APPLICATION OF COPULAS TO ANALYSIS OF EFFICIENCY OF WEATHER DERIVATIVES AS PRIMARY CROP INSURANCE INSTRUMENTS

A Thesis

by

VITALY FILONOV

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2011

Major Subject: Agricultural Economics

Applications of Copulas to Analysis of Efficiency of Weather Derivatives as Primary

Crop Insurance Instruments

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August 2011

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ABSTRACT

Applications of Copulas to Analysis of Efficiency of Weather

Derivatives as Primary Crop Insurance Instruments. (August 2011)

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Chair of Advisory Committee: Dr. Dmitry V. Vedenov

Numerous authors note failure of private insurance markets to provide affordable and comprehensive crop insurance. Economic logic suggests that index contracts may potentially have some advantages when compared with traditional (farm based) crop insurance. Hence introduction of crop insurance contracts, based on weather indexes, might be a reasonable approach to mitigate problems associated with traditional crop insurance products and possibly lower the cost of insurance for end users.

The objective of this study was to estimate the risk reducing efficiency of crop insurance contracts, based on weather derivatives (indexes) in the state of Texas. The distributions of representative farmer's profits with the proposed contracts were compared to the distributions of profits without a contract. This was done to demonstrate the risk mitigating effect of the proposed contracts. Moreover the study tried to account for a more complex dependency structure between yields and weather variables through the usage of copulas, while constructing joint distribution of yields and weather data.

Selection of the optimal copula was implemented in the out-of-sample efficient framework. An effort was made to identify the most relevant periods of the year, when weather had the most significant influence on crop yields, which should be included in the model, and to discover the most effective copula to model joint weather/yield risk.

Results suggest that effective insurance of crop yields in the state of Texas by the means of proposed weather derivatives is possible. Besides, usage of data-mining techniques allows for more accurate selection of the time periods to be included in the model than ad hoc procedure previously used in the literature. Finally selection of optimal copula for modeling of joint weather/yield distribution should be crop and county specific, while in general Clayton and Frank copula of Archimedean copula family provide the best out-of-sample metric results.

DEDICATION

Памяти любимой мамы посвящается.

This thesis is dedicated to the memory of my beloved mother.

ACKNOWLEDGEMENTS

I would like to express my deepest respect and gratitude to my adviser and committee chair, Dr. Dmitry V. Vedenov, for his support, intellectual and moral guidance and valuable suggestions during this project. He has been my academic adviser throughout the entire course of my graduate degree and has made a significant contribution to my professional development.

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Finally, thanks to my family for their encouragement and love.

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CHAPTER I

INTRODUCTION

In general, risks experienced by agricultural producers could be divided into two major categories: price risks and volumetric risks. Unless a farmer belongs to a cooperative or is a part of vertically integrated conglomerate, he/she sells products and purchase inputs in an open market, and as a price-taker is exposed to price risk, meaning that the amount of money he could charge for his commodities and is charged for his inputs wary depending on the supply-demand relationships at a given moment of time. To avoid this type of risks farmers can set up Over-The-Counter (OTC) forward contracts, or use exchange traded futures and options to hedge their exposure to price risks.

In contrast, to reduce their exposure to volumetric risks, i.e. risks of fluctuating volumes of production and sales, agricultural producers may use variety of on farm and market based instruments. For centuries farmers have been using basic on farm risk reducing techniques such as risk prevention, diversification, and creation of reserves (Hardaker, Huirne, Anderson, and Lien, 2004). The former method includes all precautionary measures aimed at avoiding or reducing exposure to various production and business risks (e.g. pest and disease control, investment in irrigation, prevention of burglary, and fire, etc.). Diversification of production program allows reducing dispersion of the overall return by selecting a portfolio of activities that have outcomes with low or negative correlations. Finally, building financial and commodity reserves

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This thesis follows the style of *Journal of Agricultural and Resource Economics*.

farmers create risk bearing potential that allows compensating the effects of unfavorable event if necessary.

Recent development of financial markets and insurance programs, actively introduced to agricultural producers, made it possible to employ market based (risk-sharing) instruments (Berg and Schmitz, 2007), including risk pooling (insurance) and risk transfer via contracting (hedging of volumetric risks with weather derivatives). Summary of existing risk-management instruments, currently employed in the agricultural industry, is presented in Figure 1.

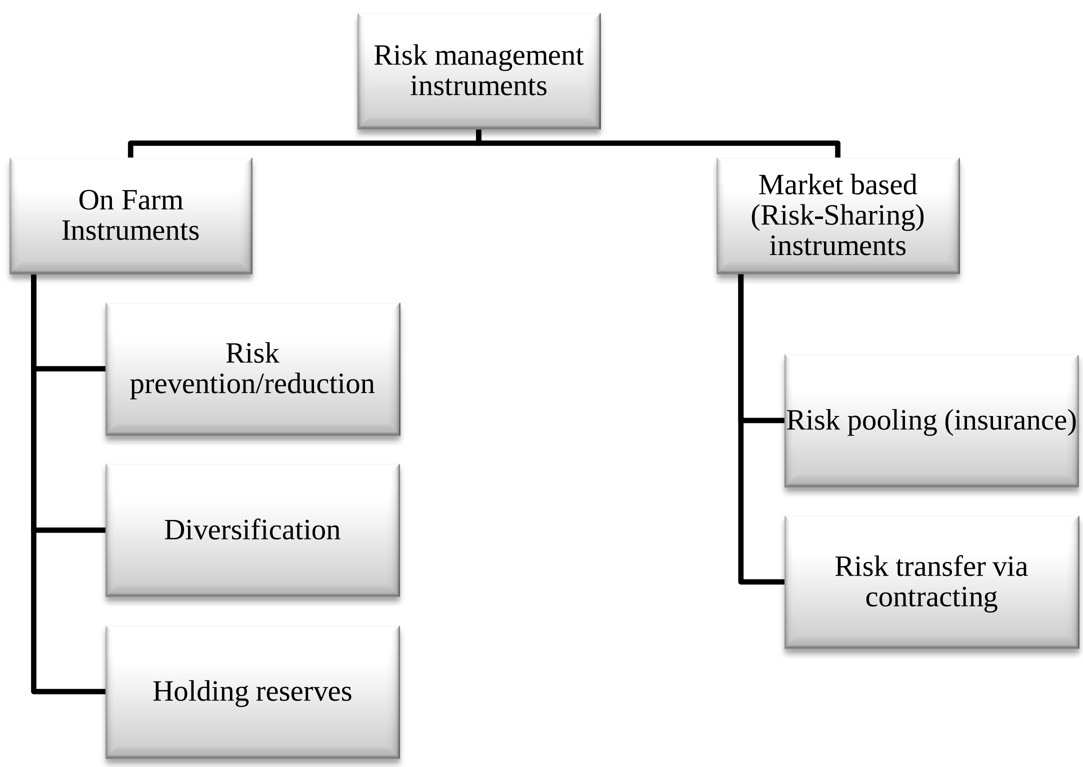

Figure 1. Risk management instruments available for agricultural producers (adapted from Berg and Schmitz, 2007)

Berg and Schmitz (2007) note that all these instruments are interdependent in the sense that the effect of a certain measure on the overall risk exposure depends on the constellation of all other instruments. But it should be obvious for practitioners that in principal risk management at a farm level requires an integrated approach, i.e. consideration of the full set of risk management instruments simultaneously for more efficient optimization of farmer's objective function.

Special attention in this thesis will be devoted to management of farmers' volumetric risks by the means of weather derivatives. There are several reasons for that. First, it is widely known that weather is one of the most important production factor and at the same time one of the greatest sources of risk in agriculture. The impact of the weather risk is not limited to crop production. The performance of livestock farms, the turnover of processors, the use of pesticides and fertilizers as well as the demand for many food products also depends on weather. Moreover it is expected that fluctuations in temperature and rainfall will increase in the wake of global climate change and thereby the volumetric risk will rise further (Musshoff, Odening, and Xu, 2009; Brockett, Wang, and Yang, 2005). Second, one of the recent trends toward the convergence of insurance and finance allowed for introduction of weather derivatives and rapid growth of weather derivatives market over the last 12 years. In spite of this fact numerous authors indicate that it is still unclear whether and to what extent weather derivatives are a useful instrument of risk management in agriculture, and that the potential effectiveness of WDs at the farm level may be limited (Vedenov and Barnett, 2004), while theoretically it is quite obvious that index insurance contracts based on weather derivatives could become one of the major risk management instrument in American agriculture. Third, many authors are noting failure of private insurance markets to provide affordable and comprehensive crop insurance, based on traditional multi-peril crop insurance (Goodwin, 2001). Only after 2004 loss ratio of national crop insurance program went down below 1.0. Miranda and Glauber (1997) attribute this to the systemic weather risk, which prevents emergence and development of independent crop insurance markets, since high correlation among individual yields causes crop insurers to bear substantially higher risk per unit of premium than other property liability and business insurers. Although weather derivatives display advantages over traditional insurance, and theoretically can effectively reduce yield variability due to weather, there is only a relatively small market for these products in agriculture (Musshoff, Odening, and Xu, 2009). Fourth, application of weather derivatives to risk management in agriculture will allow excluding weather from the error term, by which it was usually represented before in many econometric models. And finally an evidence exists that susceptibility of farms to risk will rise as a result of the increasing capital intensity of agriculture and the associated increasing debt ratio. Therefore it will become increasingly necessary for farmers to insure against weather risks (Musshoff, Odening, and Xu, 2009). Taking all this in consideration we can conclude, that perhaps risk reducing potential of weather based insurance contracts hasn’t been yet discovered to its full extend and that more thorough research on weather derivatives should be conducted.

Weather derivatives offer businesses, whose production and sales volumes are largely affected by adverse weather, an efficient protection from weather risks. In this case weather derivatives enable those businesses that are already affected by unanticipated weather swings to manage this risk, in the same way that hedgers regularly use traditional financial derivatives to hedge their risks in interest rates, equities, and foreign exchange.

Analysis of previous research, performed in the field of application of weather derivatives to risk management in agriculture, allowed to identify major gaps in the literature. First of all, more than decade after introduction of weather derivatives, there is still no definite answer if this risk reducing tool can be effectively used for risk management in agriculture. Farmers lack knowledge about weather derivatives, while market makers seem to be unsure about how to develop efficient contracts based on weather indexes; as a result currently there is virtually no market for weather based insurance contracts, allowing farmers for hedging of their volumetric risks. Significant part of this lack of knowledge and understanding could be explained by the fact that in the last ten years researchers were mainly concentrating either on pricing of weather derivatives, or on development of institutional frameworks that would be required to introduce weather-based insurance. In recent years significant attention has been given to mitigation of geographical basis risk, associated with weather derivatives. Unfortunately number of papers, researching performance of weather derivatives in reducing risk exposures in agriculture, remains quite limited.

Second, as it was mentioned before, basis risk, associated with weather derivatives, received considerable amount of academic attention in the previous couple of years. But it should be noted that while researches have carefully studied and proposed solution for mitigation of geographical basis risk, its technological (technical) part virtually was excluded from the research focus (differences between two components of basis risk will be discusses in the next section of this thesis). Significant evidence that spatial basis risk may be less important than technical basis risk when hedging volumetric risks with weather derivatives (Manfredo and Richards, 2009) creates strong foundation to reconsider this approach.

Third, majority of authors for the sake of simplicity and to avoid overloading of models with too many weather variables (usually being very limited by the number of year of available data), separated temperature and precipitation components of weather risk, and used one of them to construct weather index. While it is possible to conclude that this approach to some extent allows avoiding problems of limited data, it doesn’t permit careful capturing of weather risk, and thus, significantly reduces effectiveness of proposed contracts.

In addition, no research was found, advocating for the best selection of time frame, over which weather variables have to be recorded. Usual ad hoc approach, widely used by agricultural economists in academic publications, suggests usage of calendar periods (months or season) to construct a valid weather index contract, while agronomical publications do not provide consistent answer to this question.

Finally literature tends to rely on linear correlation between weather and yields to construct weather derivatives contracts and assess their risk reducing efficiency, while relationship between weather variables and crop yields is characterized by far more complicated structure.

Purpose of this research is to evaluate risk reducing efficiency of insurance contracts, based on weather indexes, for crop producing farmers in the state of Texas, and hopefully to fill in some gaps identified in the literature review section. The research methodology will be based on the classical paper on assessment of weather risk by Vedenov and Barnett (2004), although certain methodological improvements covering issues of appropriate weather variables selection, simulation of joint weather/yield distribution, and measurement of risk reducing efficiency of proposed contracts, will be introduced.

Assessment of risk reducing efficiency of proposed weather derivative contracts, modeled as “elementary contracts”, will be based on comparison of Lower Partial Moments of second degree of a representative farmer with and without a contract. In addition an effort will be done to account for nonlinear dependency structure between weather and yields, while simulating joint weather/yields distribution. This will be done by the means of elliptical (Gaussian, t), Archimedean (Frank, Gumbel, and Clayton) and Kernel density copulas. The most optimal copula to model the joint weather/yield distribution will be identified by optimization of out of sample log-likelihood functions (OSLL) using “leave-on-out” cross validation procedure. Also, assuming necessity to account for non-normal distribution of weather and crop yields variables, both groups of variables, used in construction of weather indexes and assessment of risk reducing efficiency of weather derivatives, will be simulated using kernel density functions.

Mitigation of technological part of basis risk, associated with weather derivatives contracts, will become a major focus of this thesis. This goal will be achieved by the means of more careful selection of time periods, used to construct weather indexes. Following nontraditional approach, instead of using calendar monthly and seasonal periods, crop growing period will be divided into weekly periods, and daily weather variables values, falling into these weeks, will be used to create weekly variables. Usage of smaller time periods weather variables will allow to identify candidate periods, which should be later included in a weather index model. Weekly weather variables will be further aggregated into 2, 3, 4 and 5 (proxy for a month) weeks, and seasonal periods. Corresponding weather indexes will be constructed using these variables, and analyzed from the perspective of their risk reducing efficiency. This will be done to compare and contrast different time periods and answer the question what is the most appropriate time period to construct an effective weather derivative contract.

Given virtually endless number of possible combinations of weather variables, which could be included in a weather index model, major difficulty associated with the proposed methodology will be a problem of appropriate time periods selection. Three data mining techniques will be employed in this analysis to identify candidate weather periods:

1. Technique 1 - based on correlation between crop yields and candidate weather periods.
2. Technique 2 - based on the smallest Akaike Information Criterion (AIC), resulting from the model, fitting crop yields and candidate weather periods.

3. Technique 3 - based on revealed causal inferences between crop yields and weather variables by the means of Directed Acyclical Graphs Methodology (DAGs).

Even though shorter time periods are more efficient in capturing brief but intensive weather events, limited sample size available for county level crop yields in state of Texas will not permit for effective explanation of weekly weather reliability. Given this fact, once optimal candidate variables are identified, an attempt will be made to create longer time periods around them, what, on one hand, will allow to include most critical weeks in the model, while one the other will provide sufficient level of data smoothing.

Exposure to geographical basis risk will be minimized by the means of using county level crop yields and weather data (Heating and Cooling Degree Day indexes and cumulative rainfall) obtained from a weather station centrally located in a given county.

Thus, this research is an attempt to fill in some gaps in the literature on weather derivatives and to improve methodology proposed by Vedenov and Barnett (2004) for assessment of risk reducing efficiency of weather derivatives.

CHAPTER II

LITERATURE REVIEW

Turvey and Norton (2008) admit that since 2000 a variety of weather insurance models, propositions, theorems, and structures have been proposed, but there is a little agreement on how a weather risk should be defined. They define weather risk as a specific event risk, which is uniquely defined at any location by the functional relationship between duration (definition in time ranging from a day, week, month, year, or more or less), frequency (probability that the event occurs over specified duration) and intensity (measure of scale and refers to the quality and condition under investigation). Brockett, Wang, and Yang (2005) describe weather risks as uncertainty in cash flows and earnings caused by noncatastrophic weather events such as temperature, humidity, rainfall, snowfall, stream flow and wind. They are contrasting weather risks with the catastrophe-related risks (CAT risks) caused by hurricanes, tornadoes, and windstorms, among others. The definition provided by the second group of researchers is more intuitive and hence will be use it for the purposes of this thesis.

Defined generally, weather derivatives are financial instruments with a value that is contingent on an underlying weather index (Manfredo and Richards, 2009)

Turvey (2001) defines two major types of contracts used to insure weather events:

1. Straightforward derivatives based upon such notions like Cooling Degree Days (CDDs), or growing degree days, or crop heat units (similar to conventional put and call options).

2. Single and multiple event contracts, which provide a fixed amount when the specific event occurs (e.g. no rain for 14 days straight during critical stages in crop development). These contracts may allow for multiple events and usually provide a fixed payoff per event.

The birth of the weather derivatives market can be traced to the trade based on the Heating Degree Days (HDD) in Milwaukee for the winter of 1997-1998, announced by Koch Industries and Enron; first exchange-based weather contracts have been introduced on Chicago Mercantile Exchange (CME) in 1999 (Brockett, Wang, and Yang, 2005).

Even though market for weather derivatives exists only for a little bit more than a decade, a considerable amount of academic work has been done on applications of weather derivatives to risk management in agriculture.

There is a general consensus among researchers and practitioners about the advantages possessed by weather derivatives, which allowed them to become one of the fastest growing derivative products on CME in 2007 (Ginocchio, 2008), among them are:

- Ability to insure damages, caused by less drastic events (e.g. insufficient rainfall), comparing to traditional insurance against damages from catastrophic events (e.g., hail).
- Absence of necessity to prove the damage to obtain indemnity payments, since payments with weather derivatives are tied to weather variables that are

measured objectively at a specified location, and hence make weather derivatives not impact-, but cause-oriented.

- Weather derivatives are more attractive from the administrative point of view, since the role of adjuster in calculating yield claims is removed, what eliminates effects of moral hazard problem. Adverse selection is minimized because premiums are based on specific events such as rainfall, which are uncorrelated with the participation rates of producers in the program, and therefore brings advantages of relatively low transaction costs for weather derivatives (Turvey, 2001).
- Weather derivatives also offer attractive opportunities for institutional investors such as insurers or banks to diversify a portfolio, since the weather-related risks are only correlated relatively weekly with the systematic risk of a national economy (Brockett, Wang, and Yang, 2005).
- Weather derivatives are usually simple to understand, as only one peril is insured.
- Weather derivatives are predictable, as the customer can follow the weather events throughout the growing season.
- Finally they are timely, since claim payments are made in the end of the insured period when the weather data values are collected (Turvey, 2001).

Majority of researchers studying relationship between weather and agricultural yields conclude that weather derivatives can allow for effective management of volumetric risks in agriculture at both primary and reinsurance levels of aggregation

(Musshoff, Odening, and Xu, 2009; Turvey, 2001; Norton, Osgood, and Turvey, 2010; Turvey, Kong, and Belltawn, 2009; Woodard and Garcia, 2008; Mahul, 2001; Vedenov and Barnett, 2004). At the same time there is still significant amount of the skepticism in the industry. Edward and Simmons (2004) note that although weather derivatives display advantages over traditional insurance, there is only a relatively small market for these products in agriculture. Norton, Osgood, and Turvey (2010) note that despite the promise of the technology it's not always straightforward to apply.

Among major factors hampering development of agricultural risk management tools based on weather indexes are:

- Farmers' unfamiliarity with weather derivatives.
- Impacts of remaining price uncertainty. Berg and Schmitz calculated (2007) that even a moderate volatility of prices cuts the risk reduction due to the weather derivative by more than half).
- Diversification effects. Farm with a broadly diversified production program don't value weather derivatives as much as highly specialized operations do (Berg and Schmitz, 2007).
- Inconsistency in practice of weather derivatives valuation methods, which doesn't allow for effective and fair pricing of contracts, and creates liquidity problems.
- Presence of spatial (or geographical) and technological (or technical) basis risk (risk that payoffs of a hedging instrument do not correspond to the underlying exposure). Both elements of basis risk lead to situations, when problems of

adverse selection and moral hazard have to be traded with problem of basis risk (Berg and Schmitz, 2007; Norton, Osgood, and Turvey, 2010).

- In addition, while weather derivative may do great job in reducing the probability of low returns, it cannot secure certain revenue because of the basis risk that is always present. Weather derivatives can therefore reduce profitability risks but they cannot insure liquidity of the enterprise (since financial disasters caused by local event, e.g. hailstorm, flood, or pest damage, are still possible). Likewise they cannot replace other types of disaster assistance (Berg and Schmitz, 2007).

Certain skepticism about the future of weather derivatives allowed a number of authors to conclude that range of countries, where weather derivatives can be used as an effective tool to manage crop risks, should be limited only to the developing world (Turvey, 2001; Skees, 2008; Miranda and Vedenov, 2001). They suggest that this innovation can make it possible to offer microinsurance to rural farmers in developing countries, which can serve a valuable function in a development intervention and may lead to more interactive benefits, such as improved access to rural credit (Norton, Osgood, and Turvey, 2010).

Obviously major problem, which needs to be solved first hand in order to start even talking about potential application of weather derivatives to risk management in American agriculture, is basis risk. In theory, geographical basis risk could be significantly reduced using triangulated weather data, or providing insureds with the flexibility to choose and combine weather stations (Turvey, 2001); another approach is to perform spatial analysis techniques on weather data to provide a historical time series in varied geographic locations (Paulson and Hart, 2006). Other researchers link microinsurance to microcredit and advocate for a central financial institution to aggregate index insurance contracts so as to average out basis risk for all actors (Miranda, and Vedenov, 2001; Woodard, and Garcia, 2008). In addition, to reduce the problem of basis risk, the hedger can use a number of "basis derivatives", including basis swaps and basis options, to hedge basis risk (MacMinn, 1999; Considine, 2000). Turvey and Norton (2008) developed an internet based tool WheatherWizard, which among its various capabilities allows for mitigation of spatial basis risk. All these approaches primarily focus on geographical basis risk.

Manfredo and Richards (2009) showed that choosing hedging instruments with the ability to mitigate nonlinear risk exposure may be the most important factor in reducing overall residual basis risk when using weather derivatives. This suggests that spatial basis risk may be less important than technical basis risk when hedging volumetric risks with weather derivatives, what basically means that choice of weather stations may be less critical in managing basis risk than properly accounting for the relationship between yields and weather. We think that this actually could be the case. There is no way geographical basis risk could ever be eliminated, unless farmers set up portable weather stations in their fields (what brings back problem of moral hazard, and increases administrative costs and cost of a program for a farmer). At the same time technological basis risk always remains with a farmer, since there are other factors apart from weather affecting yields. Thus, the best solution to the problem would be to come up with the insurance product capable of mitigating systemic weather risk a farmer is exposed to (this should be achieved by the means of insurance contract based on a weather index tied with farmer's yields as close as possible), while other risks could be insured by the means of other available in the market insurance products.

Vedenov and Barnett (2004) note that majority of the weather derivatives research is focusing either on pricing of weather derivatives, or on institutional frameworks that would be required to introduce weather-based insurance. In recent years significant attention has been given to mitigation of geographical basis risk, associated with weather derivatives. Unfortunately, number of papers researching performance of weather derivatives in reducing risk exposures remains quite limited.

Review of the literature performed for the purposes of this thesis have shown that majority of researchers separate temperature and rainfall components of weather risk and use one of the two to construct weather indexes (Musshoff, Odening, and Xu, 2009; Manfredo and Richards, 2009; Berg and Schmitz, 2007; Woodard and Garcia, 2008; Mahul, 2001), while there have been just a few papers investigating effect of joint temperature-precipitation risk on crop yields (Turvey, 2001; Vedenov and Barnett, 2004). For example (Musshoff, Odening, and Xu, 2009) note that for agricultural applications rainfall-related instruments ought to play a greater role, while Woodard and Garcia (2008) justify usage of temperature weather derivatives by the fact that on a large scale average temperature and precipitation conditions for a given region are highly negatively correlated in case of extreme events. Hence one could use one of the two to represent both. They conclude that temperature derivatives may act as a suitable substitute in hedging precipitation risk when it is most needed. We don't view this approach as the best solution and see several reasons for that. Even though this approach helps to significantly decrease number of variables included in the model, it leads to under or overestimation of weather risks due to the fact that extreme weather events, under which strong negative correlation between temperatures and precipitations could be observed, are rare, and mainly because precipitations are not characterized by high level of spatial correlation as temperatures do (Musshoff, Odening, and Xu, 2009). Thus error in weather risk assessment (particularly its rainfall part) will grow with growth in geographical basis risk.

At the same time no research advocating for the best selection of time frame, over which weather variables have to be recorded, in order to construct a weather index contract, characterized by high risk reducing ability, was found. Usually researchers use ad hoc approach and subjectively select calendar time period equal to one, or several months (Musshoff, Odening, and Xu, 2009; Vedenov and Barnett, 2004), or covering the whole season (Manfredo and Richards, 2009; Berg and Schmitz, 2007; Turvey, 2001; Woodard and Garcia, 2008; Mahul, 2001) to represent the period of time, which is most crucial for development of a plant, and hence which should be used to calculate values of weather variables. Agronomical literature doesn’t provide consistent answer to this problem as well. Given the obvious fact, that each year weather stochastically fluctuates around its normal conditions, what certainly affects planting time and all subsequent stages of plant development, and taking into account that in most cases crop yields are largely affected by short-term but relatively intensive weather events, we tend to believe that approach, which would allow for using shorter time frame for weather variables, and include both temperature and rainfall variables in the model, should provide the opportunity to better capture weather risk and increase risk reducing ability of weather index contracts proposed in this thesis.

Academic literature is also inconsistent about selection of the functional form, describing relationship between weather and crop yields. While one group of authors use classical production functions of specified form (e.g. Leontief, Cobb-Douglas) to construct weather indexes (Musshoff, Odening, and Xu, 2009; Turvey, 2001; Mahul, 2001), another advocate for usage of simple seasonal temperature derivatives in lieu of more complex monthly precipitation and temperature derivatives (Woodard and Garcia, 2008). For the purposes of this thesis research preference will be given to construction of relatively complex weather indexes, including temperature and precipitation variables, and allowing for nonlinear form of weather-yield dependency. This approach could be justified by significant evidence that relationship between weather and crop yields tends to be localized, crop dependent (Vedenov and Barnett, 2004), and hence quite complex. This fact will not permit effective capturing of weather risks by the means of simple weather index.

Another concern to be addressed in this thesis is selection of weather derivative type. Broll, Chow, and Wong (2001) and Woodard and Garcia (2008) note that since there is a general consensus about nonlinear dependence between weather and crop yields, options may do a better job in hedging of weather risks than financial instruments with linear payoff structure (e.g. futures and swaps). In addition options' positions may provide flexibility in a hedging program when risk exposure is large and nonrecurring.

Consequently, within the framework of this research, analysis of classical put options' performance, written on specified weather index and for specified location, will be conducted.

To sum up, even though there are numerous problems associated with application of weather derivatives to risk management in agriculture, but there is a general consensus among agricultural economists that these problems could be solved. To overcome these problems further research is required to understand what are the best ways to mitigate geographical and technological components of basis risk, more accurately select appropriate weather variables, and account for non-linear dependence structure between weather variables and crop yields.

CHAPTER III

METHODOLOGY

3.1 Description of elementary contract and measure of risk reduction

Following Vedenov and Barnett (2004), weather derivative contracts are modeled as an "elementary contract" with the payoff defined according to the following schedule:

$$I(i|i^*,\lambda,x) = x \times \begin{cases} 0, & if\ i > i^* \\ \frac{i^*-i}{i^*-\lambda\times i^*}, & if\ \lambda \times i^* < i < i^*, \\ 1, & if\ i \leq \lambda \times i^* \end{cases} \tag{1}$$

where i is a realization of the weather index. The contract starts paying when the index i falls below specified strike i^* (for the purposes of this research we specify strike as a historical average realization of the weather index multiplied by the coverage level selected by a farmer – 85%). Once the index falls below the limit $\lambda \times i^*$ (for simplicity purposes λ is set equal to zero; thus proposed contracts will have payoff schedule similar to traditional put options. Payoff schedule for $\lambda = 0, 0.5, 1$ is represented in Figure 2), the insured receives the maximum indemnity x, equal to the price of one bushel (or bail for cotton) of crop multiplied by the average historical theoretical yield (weather index). Values of strikes and maximum indemnity for each crop/location combination are specified in Tables A-1 - A-3 of appendix.

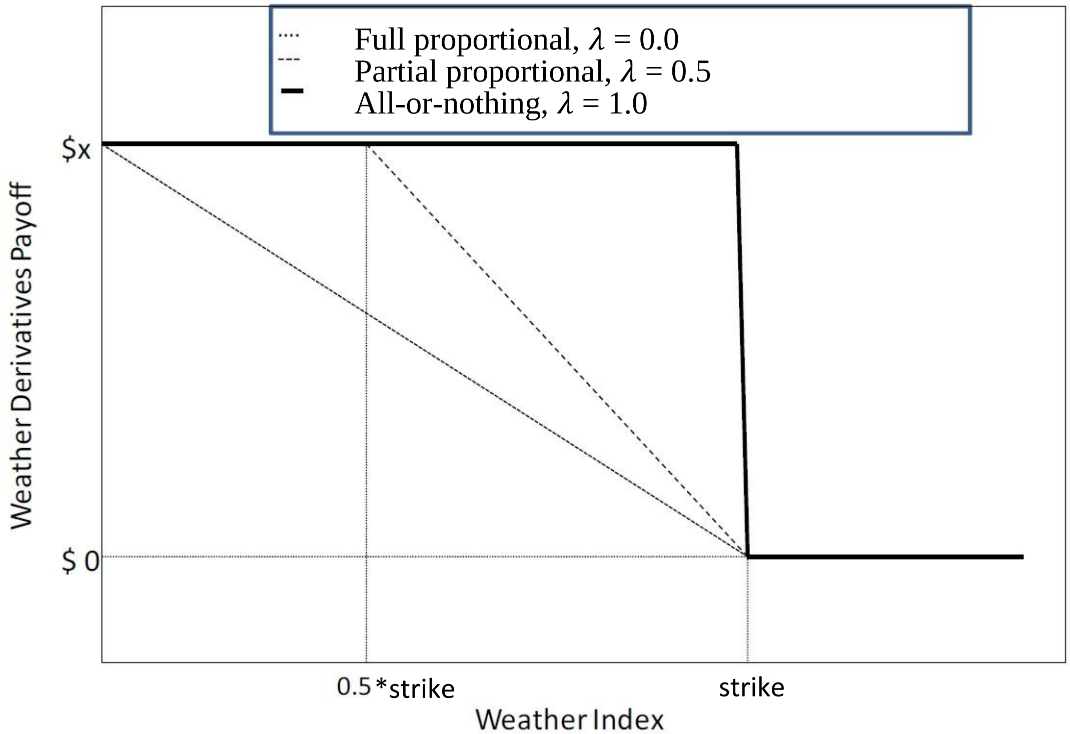

Figure 2. Payoff schedule for a weather derivative contract (adapted from Vedenov and Barnett (2004))

The actuarially-fair premium is set equal to the expected payoff of the contract, i.e.:

$$premium(x, i^*, \lambda) = \int I(i|i^*, \lambda, x)g(i)di, \tag{2}$$

where $g(i)$ is the probability distribution of the weather index. In this study it is assumed that the index can be modeled with kernel density function using Epanechnikov kernel and "rule of thumb" bandwidth.

The risk reducing effectiveness of weather derivatives as a risk management tool is evaluated using measure delta representing difference between Lower Partial Moment (LPM) measures of second degree (LPM_2) for a farmer without and with a contract.

$$delta_m = LPM_2without_m - LPM_2with_m, \tag{3}$$

where m specifies the time period over which weather variables are recorded. 1 – for 1 week, 2 – for 2 weeks, …, 5 – for 5 weeks, and 6 – for seasonal time frame.

LPM is a measure of downside risk of returns that depends only on those returns that fall below some target level of returns (Price, Price, Nantell, 1982). It is defined and measured as:

$$LPM_h\left(R_p\right) = \int_{-\infty}^{h}(R-h)^n f_p(R)dr, \tag{4}$$

where h is the target level, and $f_p(R)$ represents the probability density function of returns for asset p.

LPM of second degree (LPM_2), computed as the average of the squared deviations of profits below a target return, is more general measure of downside risk than semi-variance and for the case without a contract is calculated according to the following formula:

$$LPM_2without = \int_{-\infty}^{\bar{\pi}}(\bar{\pi} - \tilde{\pi})^2\, g(y)dy, \tag{5}$$

where $\tilde{\pi} = p \times y$ – distribution of stochastic profits without a contract (p – price of one bushel/bail of a crop, y – random realization of yields); $\bar{\pi}$ – threshold, after which a decision maker is indifferent about risk, associated with the risky alternative. For the purposes of this analysis $\bar{\pi}$ is set equal to the mean profit of a representative farmer without a contract; $g(y)$ - the probability distribution of the detrended crop yield.

For the case with the contract, LPM_2 is calculated according to the formula:

$$LPM_2 with = \iint\limits_{-\infty}^{+\infty} \max\big(\bar{\pi} - [\tilde{\pi} + I(i|i^*, \lambda, x)\big) -$$

$$-premium(x, i^*, \lambda)],0)\ ^2 g(y, i) dydi, \qquad (6)$$

where $g(y)$ and $g(y, i)$ are the univariate and joint density function of crop yield and crop yield and weather index respectively.

Graphical representation of LPM_2 for the case without a contract (upper graph) and with a contract (lower graph) as well as intuitive description of deltas is shown in Figure 3. If a farmer is better off with a contract, distribution of his profits will be shifted more to the right when compared to the case when he/she doesn't have a contract (particularly this is the case illustrated in Figure 3). This will make area below the line, representing pdf of his profits with a contract (shaded area), located to the left from the threshold $\bar{\pi}$ (lower graph), smaller than the area below the line, representing pdf of his profits without a contract, located to the left from the threshold $\bar{\pi}$ (upper graph). Consequently, the difference between two LPMs (delta) will be represented by positive values, and thus the higher the value of $delta_m$ the more efficient the weather derivative contract in hedging farmer's weather risks.

In later sections of the thesis, values of $delta_m$ are used to rank different time periods and different data mining techniques used to construct weather indexes.

In contrast with risk reduction measures implemented in Vedenov's and Barnett's (2004) research (MRSL, VAR, CE), LPMs assume fixed return threshold, what allows avoiding negative results for risk reduction measures, given the assumption that premiums, associated with a contract are actuarially-fair.

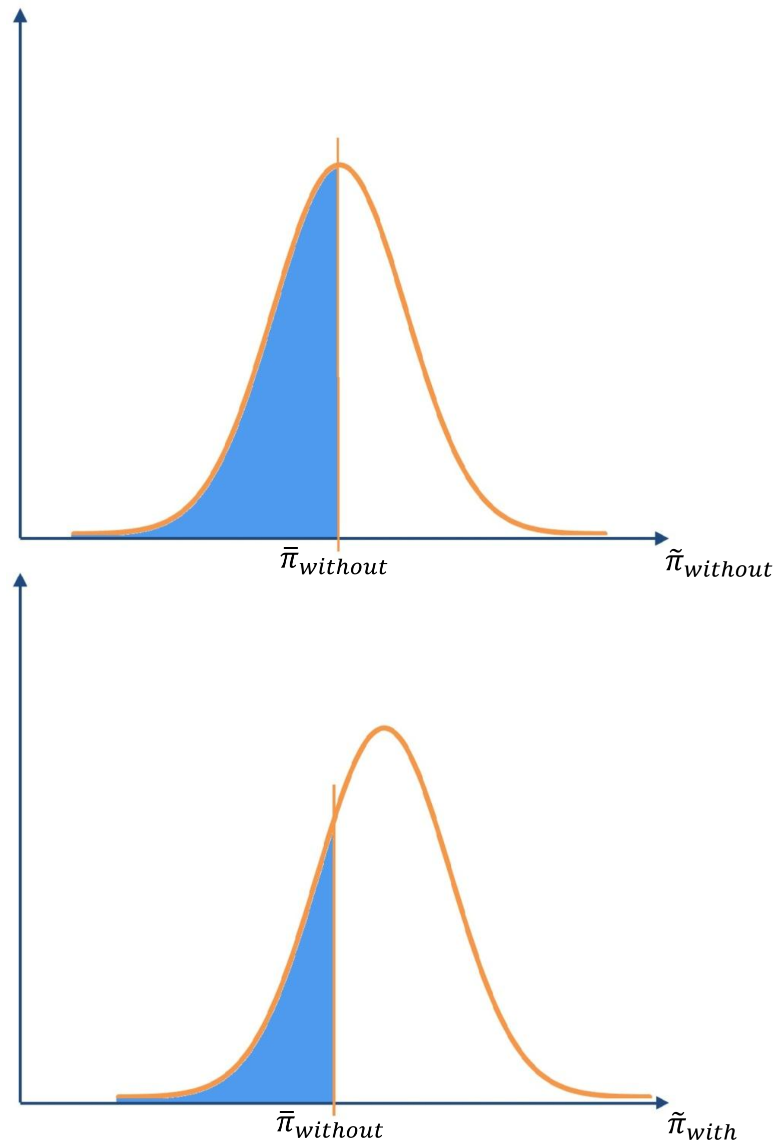

Figure 3. Graphical interpretation of LPM_2 for the case without a contract (upper graph), and with a contract (lower graph)

The univariate density functions for each crop/location combination, used in LPM_2 calculations, were estimated using Epanechnikov kernel density functions and a "rule of thumb" bandwidth. The joint distributions of indices and yields were estimated using elliptical (Gaussian and Student-t), Archimedean (Frank, Gumbel, and Clayton), and Kernel copulas and Epanechnikov kernel density marginals of crop yields and weather indexes (assuming “rule of thumb” bandwidth).

3.2 Modeling copulas

According to Cherubini, Luciano, and Vecchiato (2004) copula functions represent a methodology which has recently become the most significant new tool to handle in a flexible way the comovement between markets, risk factors and other relevant variables studied in finance.

General approach to model joint risk in the field of finance and risk management relies on multivariate distribution, which use as one of their major assumptions coefficient of linear correlation to measure dependence between two assets prices or returns. According to Rachev, Stein, and Sun (2009), the usual linear correlation is not a satisfactory measure of the dependence among different securities for several reasons. First, when the variance of returns in those securities tends to be infinite, that is, when extreme events are frequently observed, the linear correlation between these securities is undefined. Second, the correlation is a measure for linear dependence only. Third, the linear correlation is not invariant under nonlinear strictly increasing transformations, implying that returns might be uncorrelated whereas prices are correlated or vice versa. Fourth, linear correlation only measures the degree of dependence but does not clearly discover the structure of dependence. The last caveat has an especially important implication in light of the recent financial crisis. It has been widely observed that market crashes or financial crises often occur in different markets and countries at about the same time period even when the correlation among those markets is fairly low.

The structure of dependence also influences the achieved diversification benefit based on a linear correlation measure. A more prevalent approach that overcomes the disadvantages of linear correlation is to model dependency by using copulas. With the copula method, the nature of dependence that can be modeled is more general and the dependence of extreme events can be considered. Generally, a copula is used to separate the pure randomness of one variable (for example, a financial asset) from the interdependencies between it and other variables. By doing so, one can model each variable separately and, in addition, have a measure of the relations between those variables in addition. One can also choose for each and any asset in spectrum the most appropriate type of distribution, not influencing the interdependencies between those variables/assets. The interdependencies between those variables are represented by a multivariate probability distribution function, which is informative on the joint outcomes of the variables, and this multivariate distribution function is the copula.

To summarize, the use of copula allows the separation of univariate randomness (defined by the individual probability distribution functions of financial random variables) and dependence structure defined by the copula (Sklar, 1973).

There are several equivalent definitions of the copula function. Most commonly (in a bivariate case) it is defined as a bivariate distribution function with both marginal distributions being uniform on [0, 1] (Hardle, Okhrin, and Okhrin, 2008).

The bivariate copula is a function C: $[0,1]^2 \rightarrow [0,1]$ with the following properties:

- For every $u_1, u_2 \in [0,1]$ $C(u_1, 0) = 0 = C(0, u_2)$.
- For every $u_1, u_2 \in [0,1]$ $C(u_1, 1) = u_1$ and $C(1, u_2) = u_2$.
- For every $(u_1, u_2), (u_1', u_2') \in [0,1]^2$ $such\ that\ u_1 \leq u_2\ and\ u_1' \leq u_2'$

$$C(u_2, u_2') - C(u_2, u_1') - C(u_1, u_2') + C(u_1, u_1') \geq 0.$$

The separation of the bivariate distribution function into the copula function and margins is formalized in the following theorem:

Let F be a bivariate distribution function with margins F_1 and F_2, then there exists a copula C such that:

$$F(x_1, x_2) = C\{F_1(x_1), F_2(x_2)\}, x_1, x_2 \in R \tag{7}$$

If F_1 and F_2 are continuous then C is unique. Otherwise C is uniquely determined on $F_1(R) \times F_2(r)$. Conversely, if C is a copula and F_1 and $F_2$are univariate distribution functions, then function F is a bivariate distribution function with margins F_1 and F_2 (Sklar, 1973)

The theorem allows dividing an arbitrary continuous bivariate distribution into its marginal distributions and the dependency structure. The latter is defined by the copula function.

This theorem also shows how new bivariate distributions can be constructed. The class of standard elliptical distributions can be extended by keeping the same elliptical copula function and varying the marginal distributions or vice versa. Going further, one could use elliptical margins and impose some non-symmetric form of dependency by considering non-elliptical copula. This shows that copula substantially widen the family of elliptical distributions. To determine the copula function of a given bivariate distribution the following transformation could be used:

$$C(u_1, u_2) = F\{F_1^{-1}(u_1), F_2^{-1}(u_2)\},\ u_1, u_2\ \in\ [0,1], \tag{8}$$

where F_i^{-1} , i = 1, 2 are generalized inverses of the marginal distribution functions.

Since the copula function is a bivariate distribution with uniform margins, it follows that the copula density could be determined in the usual way:

$$c(u_1, u_2) = \frac{\partial^2 C(u_1, u_2)}{\partial u_1 \partial u_2},\ u_1, u_2 \epsilon [0,1] \tag{9}$$

Density function of the bivariate distribution F in terms of copula could be written as follows:

$$f(x_1, x_2) = c\{F_1(x_1), F_2(x_2)\} f_1(x_1) f_2(x_2),\ where\ x_1, x_2 \epsilon \overline{\mathbb{R}} \tag{10}$$

Currently, the most commonly used families of copulas are:

- Simplest copulas: if two random variables x_1 and x_2 are stochastically independent, the structure of such a relationship is given by the product (independence) copula:

  $$\Pi(u_1, u_2) = u_1 u_2,\ u_1, u_2 \epsilon [0,1] \tag{11}$$

  Another two extremes are the lower and upper Frechet-Hoeffding bounds (they represent the perfect negative and positive dependences respectively).

- Elliptical family: Gaussian and t-copula

  In the bivariate case Gaussian copula and its density are given by

  $$C_N(u_1, u_2, \delta) = \Phi_\delta\{\Phi^{-1}(u_1), \Phi^{-1}(u_2)\}, \tag{12}$$

$c_N(u_1, u_2, \delta) = (1-\delta^2)^{-\frac{1}{2}}\exp\{-\frac{1}{2}(1-\delta^2)^{-1}(u_1^2 + u_2^2 - 2\delta u_1 u_2)\} \times$

$\exp\{\frac{1}{2}(u_1^2 + u_2^2\}, for\ all\ u_1, u_2 \epsilon[0,1], \delta\epsilon$ (13)

In the bivariate case the t-copula and its density is given by

$C_t(u_1, u_2, \nu, \delta) =$

$\int_{-\infty}^{t_\nu^{-1}(u_1)} \int_{-\infty}^{t_\nu^{-1}(u_2)} \frac{\Gamma(\frac{\nu+2}{2})}{\Gamma(\frac{\nu}{2})\pi\nu\sqrt{(1-\delta^2)}} \times (1 + \frac{x_1^2 - 2\delta x_1 x_2 + x_2^2}{(1-\delta^2)\nu})^{-\frac{\nu}{2}-1} dx_1 dx_2,$ (14)

$c_t(u_1, u_2, \nu, \delta) = \frac{f_{\nu\delta}\{t_\nu^{-1}u_1, t_\nu^{-1}u_2\}}{f_\nu\{t_\nu^{-1}u_1) f_\nu\{t_\nu^{-1}u_2\}}, u_1, u_2, \delta\epsilon[0,1],$ (15)

where δ – correlation coefficient, ν – number of degrees of freedom, $f_{\nu\delta}$, f_ν – joint and marginal t-distributions respectively, t_ν^{-1} – quantile function of t_ν distribution.

- Archimedean family: Gumbel, Clayton, and Frank copulas.

  Opposite to elliptical copulas, the Archimedean copulas are not constructed using formula (9), but are related to Laplace transforms of bivariate distribution functions. The most useful in financial applications is the Gumbel copula with the generator and copula functions:

$\phi(x, \theta) = \exp\left(-x^{\frac{1}{\theta}}\right), 1 \leq \theta \leq \infty, x\epsilon[0, \infty]$ (16)

$C(u_1, u_2, \theta) = \exp\left[-\{(-log(u_1))^\theta + (-log(u_2))^\theta\}^{\frac{1}{\theta}}\right], 1 \leq \theta \leq$

$\infty, u_1, u_2\epsilon[0,1]$ (17)

Clayton copula with the generator and copula functions:

$\phi(x, \theta) = (\theta x + 1)^{-\frac{1}{\theta}}, 1 \leq \theta \leq \infty, \theta \neq 0, x\epsilon[0, \infty]$ (18)

$$C(u_1, u_2, \theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}, 1 \leq \theta \leq \infty, \theta \neq 0, u_1, u_2 \epsilon [0,1] \quad (19)$$

Frank copula with the generator and copula functions:

$$\phi(x, \theta) = \theta^{-1} \log\{1 - (1 - e^{-\theta}) e^{-x}\}, 0 \leq \theta \leq \infty, x \epsilon [0, \infty] \quad (20)$$

$$C(u_1, u_2, \theta) = \theta^{-1} \log \left\{ \frac{1 - e^{-\theta} - \left(1 - e^{-\theta u_1}\right)\left(1 - e^{-\theta u_2}\right)}{1 - e^{-\theta}} \right\}, 0 \leq \theta \leq \infty,$$

$$u_1, u_2 \epsilon [0,1] \quad (21)$$

- According to Vedenov (2008) an alternative approach is to use a nonparametric copula estimated from the available data. This is similar to using nonparametric techniques such as empirical distribution and kernel density estimation in a univariate case. In particular, a kernel copula can be estimated based on a multivariate analog of kernel density estimator as outlined below.

A kernel copula can be constructed from (10) by setting f equal to the kernel density estimate of the joint distribution, and f_1 and f_2 to the kernel density estimates of the corresponding marginals. A general form kernel density estimator of a univariate probability density function h can be written as:

$$\hat{f}(x, \tau) = \frac{1}{n\tau} \sum_{i=1}^{n} K\left(\frac{x - x_i}{\tau}\right), \quad (22)$$

where $\{x_i\}_{i=1}^{n}$ are observations (i.i.d. draws from the distribution being estimated), K(·) is a kernel function, and τ is a smoothing parameter called bandwidth. A bivariate analog of (22) can be written as

$$\hat{h}(x_1, x_2, \tau_1, \tau_2) = \frac{1}{n\tau_1\tau_2} \sum_{i=1}^{n} K\left(\frac{x_1 - x_{1i}}{\tau_1}, \frac{x_2 - x_{2i}}{\tau_2}\right); \quad (23)$$

There are several options for choosing the bivariate kernel function, but the most straightforward way is to use the product of two univariate (although not necessarily the same) kernels. Based on (10), (22), and (23) the overall procedure for estimating the kernel copula from a series of historical data $\{x_{1i}, x_{2i}\}_{i=1}^{n}$ can be outlined as follows:

Step 1. Construct the kernel density estimates of marginal distributions f_1 and f_2 according to (22) using appropriate kernels K_j and bandwidths τ_j.

Step 2. Calculate the cumulative density functions corresponding to f_1 and f_2 (e.g. by numerical integration)

$\widehat{F}_1(x_1) = \frac{1}{n\tau_1}\int_{-\infty}^{x}\sum_{i=1}^{n} K_1(\frac{\xi - x_{1i}}{\tau_1})\, d\xi$

and $\widehat{F}_2(x_2) = \frac{1}{n\tau_2}\int_{-\infty}^{x}\sum_{i=1}^{n} K_2(\frac{\eta - x_{2i}}{\tau_2})\, d\eta$; (24)

Step 3. Construct kernel density estimate of the joint density h according to (23) using the product kernel and the same bandwidth as in Step 1.

Step 4. Estimate the copula density at any given point (u_1, u_2) based on (10), namely

$$\hat{c}(u_1, u_2) = \frac{\hat{h}(\hat{F}_1^{-1}(u_1), \hat{F}_2^{-1}(u_2))}{\hat{f}_1(\hat{F}_1^{-1}(u_1)) \times \hat{f}_2(\hat{F}_2^{-1}(u_1))}, \tag{25}$$

where $\hat{F}_1^{-1}(u_1)$, and $\hat{F}_2^{-1}(u_2)$ are inverse functions of the cumulative densities estimated in (24), which can be obtained by solving numerically the root-finding problems $\hat{F}(x_1) = u_1$, and $\hat{F}(x_2) = u_2$ for giver u_1 and u_2 respectively.

Once estimated, the kernel copula can be combined with any estimated of the marginal distributions of f_1 and f_2, either parametric or nonparametric.

3.3 Construction of weather index

Value of any derivative contract is derived from the value of its underlying asset. Hence to value and later asses effectiveness of weather derivatives the asset, from which its value is derived, should be defined. As it was noted above weather derivatives are a type of financial contracts, which payments are contingent on value of underlying weather index. Major specifications of these contracts include variable(s) used to derive value of the underlying asset, location of weather station, where these variables are recorded, functional form, describing dependency between separate weather variables and weather index as a whole, duration of the contract, and time of maturity.

Analysis of effectiveness of weather derivatives creates an endless number of possible crop/location combinations. For the purposes of this thesis scope of the research will be limited to the state of Texas, and particularly to four geographically and climatically distinct areas. Analysis conducted by Vedenov and Barnett (2004) was unable to identify significant risk reducing effect of weather derivatives contracts specified in their research. This could partially be attributed to significant effect of geographical basis risk, since in their analysis they've been using Crop Reporting District (CRD) level yields and weather data from centrally located to those CRDs weather stations. In this thesis an attempt will be made to reduce geographical basis risk by the means of using county level yields and weather data, obtained from the weather station centrally located in the given county. Three major crops produced in Texas: corn, winter wheat, and cotton, will serve as objects of the analysis. Table 1 lists all possible crop/county combinations and corresponding weather stations. Selection of counties for analysis was based on presence of large non-irrigated production of crops of interest in these territories (except for Panhandle area where virtually all agricultural production is irrigated). Majority of selected counties are leading producers of non-irrigated crops in these areas.

Table 1. Areas, crops, counties, and weather stations selected for analysis

Area	Crop	County	Weather station name	COOP ID
Panhandle	Corn	Castro	Dalhart municipal airport	412240
	Wheat	Ochiltree	Perryton	416950
	Cotton	Lubbock	Lubbock international airport	415411
East from Panhandle	Corn	Williamson	Georgetown lake	413507
	Wheat	Haskell	Haskell	413992
	Cotton	Haskell	Haskell	413992
East and Central Texas	Corn	Robertson	Franklin	413321
	Wheat	Bell	Stillhouse Hollow Dam	418646
	Cotton	Robertson	Franklin	413321
Coastal Area	Corn	Wharton	Pierce 1 E	417020
	Wheat	Bee	Beeville 5 NE	410639
	Cotton	Wharton	Pierce 1 E	417020

To construct weather index weather variables, on which these contracts will be based, need to be defined. Heating Degree Days index (HDD), Cooling Degree Days index (CDD), and cumulative precipitations are chosen as weather variables of choice. Major reason to use degree day indices over average temperature was their higher potential liquidity, and thus higher possibilities for these contracts to be used not only by farmer, but also by risk reinsurers. The question if 65F is relevant reference point to calculate degree days indexes for weather derivatives used in agriculture, remains open.

HDDs and CDDs were calculated according to the following formula:

$$HDD\_1week_j = \sum_{i=1}^{n} \max(0, 65 - \frac{T\_max_i + T\_min_i}{2}) \quad (26)$$

$$CDD\_1week_j = \sum_{i=1}^{n} \max(0, \frac{T\_max_i + T\_min_i}{2} - 65) \quad (27)$$

where j – number of periods in a year; T_max_i, T_min_i – are maximum and minimum air temperature recorded during day i of period j at a given weather station; n – number of days in the period.

Cumulative rainfall index was calculated according to the following formula:

$$R\_1week_j = \sum_{i=1}^{n} rainfall_i, \quad (28)$$

where $rainfall_i$ – rainfall recorded during day i of period j at a given weather station.

According to Woodard and Garcia (2008) relationship between temperatures and yields is likely nonlinear and quadratic; Manfredo and Richards (2009) was able to show the same dependence structure for precipitations and yields. Thus the functional form of a model, which will be used to estimate values of weather index, is represented by the following formula:

$$log_e(yield_{detr\_i}) = \beta_0 + \sum_{j=1}^{6}[\beta_j \times log_e(W_{j_i}) + \beta_{j+6} \times (log_e(W_{j_i})^2] + \varepsilon_i, \quad (29)$$

where $yield_{detr\_i}$ – detrended crop yields in year i, estimated by the means of the following formula (Vedenov and Barnett, 2004):

$$yield_{detr\_t} = yield_t \times \hat{y}ield_{2008} / \hat{y}ield_t, \quad (30)$$

where $yield_{detr\_t}$ – detrended values of yield in year t, $yield_t$ – value of yield in year t from the initial vector of yields, $\hat{y}ield_{2008}$ – the last value of yield in the vector of forecasted yields, $\hat{y}ield_t$ – value of yield in year t in the vector of forecasted yields, W_{j_i} – weather variable j recorded during specified time period in year i.

Even though many authors advocate for necessity to avoid uniformity in design of weather derivatives (Turvey, 2008; Berg, Schmitz, 2007), they still tend to use uniform approach for different crops and different territories defining the time frame, during which weather is supposed to have critical influence on crop yields, setting it equal to calendar month (e.g. May, June, July, August) or calendar season (e.g. June-August). There are at least three significant reasons to deviate from this approach. First, weather events characterized by relatively short duration and high intensity tend to have most significant event on crop yields. For example temperature stress (heat or frost), experienced by a plant during several hours, may significantly decrease its agronomic properties. At the same time, short and not intensive showers recorded over the whole growing season may accumulate to a significant amount, but in fact they could be not sufficient for normal development of a plant in case of hot temperatures and high evaporation. In contrast relatively short but intensive rain in combination with moderate temperature regime will result in the same cumulative value recorded over the growing season, but in fact may provide high soil moisture necessary for normal development of a crop, if this rain happens at the right time. Second, in spite of the fact that it takes for the Earth to rotate around the Sun virtually the same amount of time each time it does so, there is a chance for micro fluctuations in Earth's orbit, resulting in changes in its atmosphere, what makes each year to be slightly different from the previous one from the hydro meteorological point of view. Hence there is no evidence to believe that each year planting time and most important periods of plant development will happen at the same time. Consequently usage of calendar monthly or seasonal time periods may be not the most efficient way to account for weather risks (e.g. in one year corn tasseling may start during the last week of June, while in the other it may begin in the first week of July). And finally agronomic practice shows that even within one state planting time and speed of plant development may wary in different parts of the state. The difference could range anywhere from 1-2 weeks to a month. See Table 2 (Bowman and Lemon, 2006; Goffman, 1998; Warrick and Miller, 1999; Miller, 1999).

Table 2. Growing period dates typical for crops produced in different parts of Texas

Area	Crop	Plant development stage	Average time frame
Panhandle	Corn	Planting and emerging	Mid April - Mid May
		6-8 leaf stage through tasseling	Late May - Mid July
		Tasseling through dent	Mid July - Mid September
	Wheat	Planting and emerging	Mid October - Mid November
		Booting through dough	Mid March - Late May
		After dough period	Late May - Late August
	Cotton	Planting and emerging	Mid May - Mid June
		Squaring through blooming	Mid June - Mid August
		Fruiting through first open bowl	Late August - Late October

Table 2 continued

Area	Crop	Plant development stage	Average time frame
East from Panhandle	Corn	Planting and emerging	End of February - Mid March
		6-8 leaf stage through tasseling	Early April - Late April
		Tasseling through dent	Early May - Mid July
	Wheat	Planting and emerging	Mid October - Mid November
		Booting through dough	Mid March - Late May
		After dough period	Late May - Late August
	Cotton	Planting and emerging	Mid May - Mid June
		Squaring through blooming	Mid June - Mid August
		Fruiting through first open bowl	Late August - Late October
East and Central Texas	Corn	Planting and emerging	End of February - Mid March
		6-8 leaf stage through tasseling	Early April - Late April
		Tasseling through dent	Early May - Mid July
	Wheat	Planting and emerging	Mid October - Mid November
		Booting through dough	Mid March - Late May
		After dough period	Late May - Late August
	Cotton	Planting and emerging	Early April - Late April
		Squaring through blooming	Late April - Late June
		Fruiting through first open bowl	Early July - Late August
Coastal area	Corn	Planting and emerging	End of February - Mid March
		6-8 leaf stage through tasseling	Early April - Late April
		Tasseling through dent	Early May - Mid July
	Wheat	Planting and emerging	Mid October - Mid November
		Booting through dough	Mid March - Late May
		After dough period	Late May - Late August
	Cotton	Planting and emerging	Late February - Late March
		Squaring through blooming	Late March - Late May
		Fruiting through first open bowl	Early June - Late July

This allows concluding that more accurate accounting for weather, affecting yields, should be a crucial part of the process of weather derivatives contracts development, and, if done correctly, could significantly contribute to higher efficiency of these contracts.

Just as calendar months or season being too long for accurate assessment of weather risks, daily periods won't increase accuracy of this analysis (one day is not always enough for weather to start negatively affecting yields, particularly in the case of precipitation risks), but will significantly affect complexity of calculations. Hence for the purposes of this thesis weekly periods will be used as a basic time frame over which weather variables will be recorded. Weeks offer enough flexibility without significant complications of calculations. An attempt will be done to use two, three, four and five (as a proxy to one month) weeks periods within a growing season, as well as seasonal period (in contrast with calendar season we will use growing period season defined in Table 3) to create a methodological framework, which could help answering the question what is the optimal length of time frame, over which weather derivatives contract should be constructed (see formulas below).

$$HDD\_2week_k = HDD\_1week_j + HDD\_1week_{j+1} \tag{31}$$

$$CDD\_2week_k = CDD\_1week_j + CDD\_1week_{j+1} \tag{32}$$

$$R\_2week_k = R\_1week_j + R\_1week_{j+1}\ , \tag{33}$$

where j = 1, 2, 3, …, 51 – number of the week, k = j – number of two-weeks period.

$$HDD\_3week_k = HDD\_1week_j + HDD\_1week_{j+1} + HDD\_1week_{j+2} \tag{34}$$

$$CDD\_3week_k = CDD\_1week_j + CDD\_1week_{j+1} + CDD\_1week_{j+2} \tag{35}$$

$$R\_3week_k = R\_1week_j + R\_1week_{j+1} + R\_1week_{j+2} \tag{36}$$

where j = 1, 2, 3, …, 50 – number of the week, k = j – number of three-weeks period.

$$HDD_{4week_k} = HDD_{1week_j} + HDD_{1week_{j+1}} +$$

$$+ HDD\_1week_{j+2} + HDD\_1week_{j+3} \tag{37}$$

$$CDD_{4week_k} = CDD_{1week_j} + CDD_{1week_{j+1}} +$$

$$+ CDD\_1week_{j+2} + CDD\_1week_{j+3} \tag{38}$$

$$R\_4week_k = R\_1week_j + R\_1week_{j+1} + R\_1week_{j+2} + R\_1week_{j+3} \tag{39}$$

where j = 1, 2, 3, …, 49 – number of the week, k = j – number of three-weeks period.

$$HDD_{5week_k} = HDD_{1week_j} + HDD_{1week_{j+1}} + HDD_{1week_{j+2}} +$$

$$+ HDD\_1week_{j+3} + + HDD\_1week_{j+4} \tag{40}$$

$$CDD_{5week_k} = CDD_{1week_j} + CDD_{1week_{j+1}} + CDD_{1week_{j+2}} +$$

$$+ CDD\_1week_{j+3} + +CDD\_1week_{j+4}; \tag{41}$$

$$R_{5week_k} = R_{1week_j} + R_{1week_{j+1}} + R_{1week_{j+2}} +$$

$$+ R\_1week_{j+3} + R\_1week_{j+4} , \tag{42}$$

where j = 1, 2, 3, …, 48 – number of the week, k = j – number of three-weeks period.

For the purposes of this research calendar year has been divided into 52 weeks, starting with September 1 for winter wheat and January 1 for corn and cotton. Growing seasons for all three crops include periods specified in Table 2 plus one month before beginning of the period and one month after its end to account for pre-planting soil moisture accumulation and maturation of crops respectively (see Table 3).

Selection of appropriate variables, which should be included in the regression model to calculate values of weather index, is not a trivial task, since model should guarantee relatively high level of correlation between yield variations and corresponding payoffs from the weather derivative. To be able to successfully solve this problem several data mining techniques will be employed for the purposes of this research to determine optimal set of temperature and precipitation variables to be included in the model.

Table 3. Time period used in data mining to select most crucial weather variables

Area	County	Crop	Time period used in data mining procedure
Panhandle	Castro	Corn	Mid March - Late October
	Ochiltree	Wheat	Mid September - Late August
	Lubbock	Cotton	Mid April - Late November
East from Panhandle	Williamson	Corn	Early February - Late August
	Haskell	Wheat	Mid September - Late August
	Haskell	Cotton	Mid April - Late November
East Texas	Robertson	Corn	Early February - Late August
	Bell	Wheat	Mid September - Late August
	Robertson	Cotton	Early March - Late September
Coastal Area	Wharton	Corn	Early February - Late August
	Bee	Wheat	Mid September - Late August
	Wharton	Cotton	Early February - Late August

Three different approaches will be compared and contrasted to select optimal set of weather variables. The same functional form for construction of a weather index for all 3 approaches and all crop/location combinations outlined above has been used to allow for reasonable comparison of results.

In the ideal world all available weather variables would be included in the model, since it is a legitimate assumption that all weather, observed during the growing season, have influence on the final yield. Unfortunately being limited by slightly more than 40 observations, maximum number of variables to be included in the model needs to be defined. Taking into account number of years of available data, six weather variables plus their squared terms should leave sufficient amount of degrees of freedom required to come up with a model, characterized by acceptable goodness of fit and predicting ability.

3.4 Data mining technique 1: correlation

The first data mining technique, used for the purposes of this thesis, is based on simple correlation between detrended yields and weather variables (statistically significant trend in weather variables for specified weather stations was not found). It is a legitimate assumption that there are certain periods of the year, when the weather is more critical for development of a crop then during the others, and that these periods could be picked by analysis of correlation tables between weather variables and detrended crop yields. The growing period was divided into 3 parts, as they are defined in Table 2. One temperature index and one precipitation variable from each period which have highest correlation with detrended yield (6 variables in total) was picked and plugged into equation 29 to come up with theoretical values of weather indexes, which will be used as an underlying asset of proposed weather derivatives contract. Choice of 3 periods within growing period (as they are defined in Table 2) is justified by a mere fact that periods covering planting and emergence of a plant (period 1), vegetative stage (period 2), and reproductive stage of plant development (period 3) should be represented by at least 1 temperature and 1 precipitation variable in order to properly account for weather risk.

This approach is applied to all possible time periods specified above, over which weather variables could be recorded (see formulas 22-24, 27-38), and corresponding weather indexes are constructed.

Application of this technique is extended by the means of cross validation of resulting models for each time frame in order to test their out-of-sample efficiency and determine the time frame which generates the model, characterized not only by the highest goodness of fit, but also by low out-of-sample forecasting error. To do this "leave-one-out" cross validation technique (LOOCV), also known as jackknife, was employed (Mosteller and Tukey, 1977). Mean squared error is used as a measure of out-of-sample fit. This extension might be a reasonable approach to answering the question what is the time frame generating the most efficient weather derivatives contracts.

Major advantages of this data mining technique are its relative simplicity, expressed in small computational time required for construction of weather indexes, and ability to test out-of-sample efficiency of resulting models. Major disadvantages are that it is based on subjective division of growing period into three parts and picking of one temperature and one precipitation variable from each period using criterion of linear correlation between weather and yields (which is, as it was shown by previous researchers, most often is not the case in agriculture).

3.5 Data mining technique 2: lowest AIC

Second data mining technique used in this research is based on blind selection of weather variables, resulting in the model, characterized by the lowest Akaike Information criterion (AIC), calculated by fitting historical detrended yields and degree days indexes and cumulative precipitations, recorded over specified time frames.

AIC is calculated according to the following formula:

$$AIC_m = -2 \times \ln(L_m) + 2 \times K_m, \qquad (43)$$

where AIC_m – AIC for the m-th model of M alternative models; K_m – number of independent parameters estimated for the m-th model; $\ln(L_m)$ – sample log-likelihood for the m-th model.

For the purposes of this approach the growing period is not split into three parts. Instead all weather variables are pulled in one large weather matrix and selection of any six variables resulting in the model, specified according to formula 25, with the lowest AIC is allowed. Even though this leads to enormously large and in most cases useless number of possible combinations (e.g to pick the best model for winter wheat based on 1 week weather variables, more than 320 million combinations have to be analyzed) this approach allows to make sure that no variables are missed during the process of index specification. The same procedure is repeated for all time frames to construct corresponding indexes. Major advantage of this method is ability to account for all possible combinations of weather variables included in the model, and possibility to construct weather index minimizing technological basis risk. Major disadvantages of the method are its expensiveness from a computational point of view, high chance to end up with over fitted model, and inability to account for out-of-sample performance in its current design.

3.6 Data mining technique 3: PC-algorithm

Third data mining technique implemented in this research is based on algorithm of inductive causation using directed acyclic graphs (DAGs). DAGs originally came from mathematics and computer science. The relevance of this methodology to identification of relevant weather variables to be included in the model stems from the fact that it facilitates the inference of causal relationships from observational data (Chong, Zay, and Bessler, 2010). Spirtes, Glymour, and Scheines (2000) have incorporated the notion of d-separation into an algorithm (PC Algorithm) for building directed acyclic graphs, using the notion of sepset. PC algorithm, embedded in the software TETRAD IV, is used for the purposes of this research to reveal causal relationships among variables. More advanced versions of PC algorithm are described as the Modified PC Algorithm, the Causal Inference Algorithm and the Fast Causal Inference Algorithm. For the purposes of this research we restrict our discussion to the PC algorithm, as it is the most basic and easily understood version (Bessler, 2003).

Bessler (2003) provides good summary of PC algorithm and conditions, required to avoid construction of the counterfactual random variable model. Generally, when applying PC algorithm, one starts with creating a complete undirected graph G on the vertex set V. The complete undirected graph shows undirected edges between every variable of the system (every variable in V). Zero correlation or partial correlation (conditional correlation) is used as a basis to sequentially remove edges between variables. To test if conditional correlations are significantly different from zero one should use Fisher's z-statistic:

$$z(\rho(i,j|k)n) = \frac{1}{2} \times (n - |k| - 3)^{\frac{1}{2}} \times \ln\{(|1 + \rho(i,j|k)|) \times (1 - \rho(i,j|k)|)^{-1}\}, \quad (44)$$

where n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j) and |k| is the number of variables in k (that we condition on). If i, j and k are normally distributed and $r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n) - z(r(i,j|k)n)$ is standard normal.

Finally, to direct the remaining edges notion of sepset is used. The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set). For the purposes of illustration, edges are directed by considering triples X — Y — Z, such that X and Y are adjacent just as Y and Z are, but X and Z are not adjacent. Direct edges between triples: X — Y — Z as X → Y ← Z if Y is not in the sepset of X and Z. If X → Y, Y and Z are adjacent, X and Z are not adjacent and there is no arrowhead at Y, then orient Y — Z as Y → Z. If there is a directed path from X to Y and an edge between X and Y, then direct (X — Y) as X → Y.

Spirtes, Glymour, and Scheines (2000) lists conditions required to avoid construction of counterfactual random variable model:

1. Requirement of causally sufficient set of variables. This means that there are no omitted variables that in fact cause any two of the included variables under study. If variable Y and Z are both caused by X and X is removed from the analysis, then probable causal flow from Y to Z (or vice versa) may be because X causes both Y and Z, so the causal flow, when Y causes Z should be considered as spurious.
2. Requirement to constrain to causal flows that respect a causal Markov condition. If X causes Y and Y causes Z, the underlying probability distribution can be factored on X, Y and Z as $\mathrm{Pr}(X, Y, Z) = \mathrm{Pr}(X). \mathrm{Pr}(Y|X)\mathrm{Pr}(Z|Y)$. Hence, causal flows are required to fulfill a genealogy condition, which says that in order to fully capture the probability distribution generating any variable one need only to condition on parents. Conditioning on grandparents, uncles or aunts, or siblings is not necessary.
3. Faithfullness requirement. Probabilities which attempted to be captured by graph G are faithful to G if X and Y are dependent if and only of there is an edge between X and Y. The faithfullness assumption states that if one observes zero correlations, it is only because the edge is not present and not because of removing deep parameters from the underlying structural model.

In some situations causal sufficiency, Markov and faithfulness conditions can be violated. Thus any result based on observational data must be viewed with caution. The causal sufficiency condition suggests that one find a sufficiently rich set of theoretically relevant variables upon which to conduct an analysis. If a relevant variable is not included in the model, one may assume that there is an edge between variables when in reality both are effects of an omitted third variable.

Even though PC algorithm is not an ideal tool for the problem being researched here, it allows for identification of crucial variables based not on criterions of simple correlation or goodness of fit, but on causal relationships among variables.

To implement this methodology in my research I don't split a growing period into three parts, and try to identify causal relationships separately between detrended yields and degree days indexes, and yields and cumulative rainfall recorded over specified time period. We start with one week weather variables, and repeat the same procedure for the remaining time periods. Weather variables directly causing yields are later used to construct weather index using formula 25.

PC algorithm is based on classical hypothesis testing and, thus, is subject to errors of commission and omission in both edges and direction, particularly in the case of small sample sizes (problems may occur in sample sizes less than 500). To avoid this problem I follow Spirtes, Glymour, and Scheines (2000) recommendations and apply an inverse relationships between sample size and p-values for removing edges, i.e. make sure that significance level used in making decisions increases as the sample size decreases (e.g. 0.2 at sample sizes less than 100). Examples of DAGs among detrended winter wheat yields in Haskell county and degree day variables and cumulative precipitation variables, recorded over time frame equal to 1 week, are presented in Figures 4 and 5.

Once variables, having direct causal effect on detrended yields, are identified, they are plugged into equation 25 to estimate values of weather index and goodness of fit between the index and detrended yields.

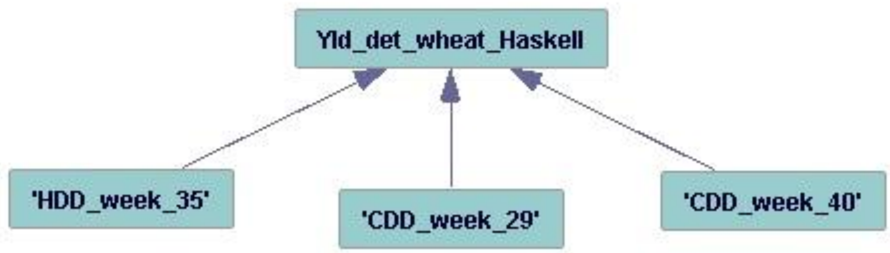

Figure 4. TETRAD IV output for 1 week temperature variables directly affecting detrended wheat yields in Haskell County

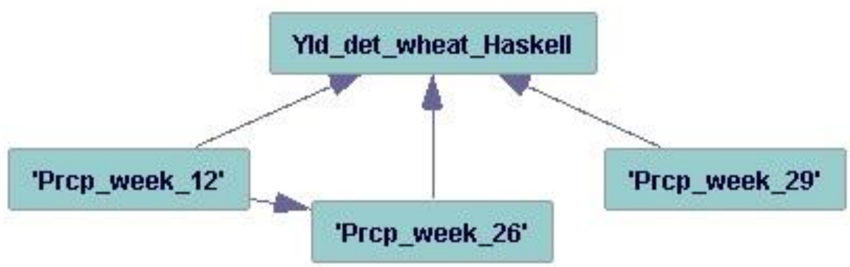

Figure 5. TETRAD IV output for 1 week precipitation variables directly affecting detrended wheat yields in Haskell County

Major advantage of this method is ability to statistically reveal causal relationships between yields and weather. Major disadvantages are its computational expensiveness, low flexibility, resulting in inability to test its out-of-sample efficiency.

3.7 Data description

National Agricultural Statistical Service of USDA (USDA/NASS, 2010) served as a source of county level crop yield data, covering period of 1968 to 2009 (unfortunately no county level yield data in Texas is available before 1968); daily weather data (both average temperatures and precipitations), covering the same period as crop yields, was obtained through National Climatic Data Center of National Oceanic and Atmospheric Association (NOAA/NCDC, 2010). An effort has been done to avoid any gaps in weather data.

CHAPTER IV

DISCUSSION OF RESULTS

All three data mining techniques, described in discussion of methodology, allowed to construct weather indexes, resulted in positive risk reduction effect for a representative farmer. Table 4 summarizes best model from each technique selected based on a criterion of highest risk reduction capacity measured by delta for the cases of Gaussian and t copula. As it is evident from the Table 4, for the area located to the east from Panhandle, and for the crops used for the purposes of this research, weather derivatives based on smaller time periods tend to outperform contracts using weather variables recorded over longer period of time, what proofs our initial hypothesis that careful selection of smaller time periods could increase efficiency of weather derivatives. The only two exceptions are indexes resulted from data mining technique based on linear correlation between yields and weather variables for winter wheat in Haskell county, and from technique based on PC algorithm for cotton in Haskell county, where longer time periods are preferred to shorter. At the same time data mining technique based on creation of the model, providing the lowest AIC values, tend to have highest risk reducing efficiency measured in relative terms, except for cotton grown in Williamson county where it is as good as technique based on PC algorithm. On average this technique allowed for construction of a weather derivatives which could potentially reduce risk of a representative farmer by 20%.

Table 4. Risk reduction efficiency of proposed contracts, based on the best model

Data mining technique	Wheat_Haskell					
	Best model	R-square	Absolute value of risk reduction		Relative value of risk reduction	
			G copula	t copula	G copula	t copula
Technique 1 (Correlation)	5 weeks or seasonal	0.64	90.06	107.24	13.4%	15.9%
Technique 2 (AIC)	3 weeks or 1 week	0.76	140.59	152.36	20.9%	22.6%
Technique 3 (PC-algorithm)	2 weeks	0.69	104.39	119.98	15.5%	17.8%
Data mining technique	Cotton_Haskell					
	Best model	R-square	Absolute value of risk reduction		Relative value of risk reduction	
			G copula	t copula	G copula	t copula
Technique 1 (Correlation)	1 week	0.51	454.37	576.80	10.0%	12.7%
Technique 2 (AIC)	1 week	0.72	1010.99	1069.16	22.3%	23.6%
Technique 3 (PC-algorithm)	4 weeks	0.51	484.43	585.31	10.7%	12.9%
Data mining technique	Corn_Williamson					
	Best model	R-square	Absolute value of risk reduction		Relative value of risk reduction	
			G copula	t copula	G copula	t copula
Technique 1 (Correlation)	1 week	0.62	895.06	947.31	15.4%	16.3%
Technique 2 (AIC)	1 week	0.76	1317.55	1315.47	22.6%	22.6%
Technique 3 (PC-algorithm)	1 week	0.75	1367.71	1365.86	23.5%	23.5%

Finally contract based on t-copula tend to outperform contracts, which efficiency was estimated using Gaussian copula. These could be attributed to the structure of dependence between weather index and yield, and ability of t-copula to capture this structure in a more efficient way.

Analysis of variables selected by each technique allows concluding that all three of them tend to pick quite similar set of variables (Tables A4-A12 of appendix). There will be at least one or two variables represented in efficient sets, picked by each technique. This could be an indicator that all three techniques are a valid way to identify candidate periods, which should be selected for construction of a weather index.

The fact that smaller time periods result in more efficient weather derivatives, based on weather indexes estimated only in-sample, doesn't necessarily mean that these indexes will work as well out-of-sample. Technique based on linear correlation between yields and weather variables allows for testing of out-of-sample efficiency of resulting weather index models. Table 5 shows that out-of-sample weather index model based on longer time periods will outperform models based on shorter periods.

Table 5. Out-of-sample mean squared error (OOS MSE) for weather indexes models, based on weather variables of variable length

Model	OOS MSE_Haskell wheat	OOS MSE_Haskell cotton	OOS MSE_Williamson corn
1 week	1.83	7.83	10.41
2 weeks	3.39	6.99	7.75
3 weeks	2.89	5.27	9.75
4 weeks	2.27	5.48	9.57
5 weeks	1.63	5.48	6.66
seasonal	1.12	3.47	4.94

Taking into account importance of criterions of out-of-sample efficiency, the next step of the research is to use candidate weather variables picked by the most in-sample efficient model (i.e. model based on weekly periods) to identify clusters of weather variables, which could be aggregated into periods of bigger size. For example, given set of efficient variables for corn grown in Haskell county, selected by different data mining techniques (Tables 6-8), two weeks could be added before each selected week and two weeks after to obtain the length of the final period, over which weather variables should be recorded to result in proxy for out-of-sample efficient weather derivate contract (Table 9). Orange color of the cell means that given week produced candidate CDD variable, dark blue – HDD variable, light blue – precipitations variable, grey – HDD and precipitation variable, pink – CDD and precipitation variable; green cell means that given cell is a part of growing season.

Table 6. Selected variables for data mining technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1/1	1/8	1/15	1/22	1/29	2/5	2/12	2/19	2/26	3/5	3/12	3/19	3/26
Last day	1/7	1/14	1/21	1/28	2/4	2/11	2/18	2/25	¾	3/11	3/18	3/25	4/1
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	4/2	4/9	4/16	4/23	4/30	5/7	5/14	5/21	5/28	6/4	6/11	6/18	6/25
Last day	4/8	4/15	4/22	4/29	5/6	5/13	5/20	5/27	6/3	6/10	6/17	6/24	7/1
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	7/2	7/9	7/16	7/23	7/30	8/6	8/13	8/20	8/27	9/3	9/10	9/17	9/24
Last day	7/8	7/15	7/22	7/29	8/5	8/12	8/19	8/26	9/2	9/9	9/16	9/23	9/30
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	10/1	10/8	10/15	10/22	10/29	11/5	11/12	11/19	11/26	12/3	12/10	12/17	12/24
Last day	10/7	10/14	10/21	10/28	11/4	11/11	11/18	11/25	12/2	12/9	12/16	12/23	12/30

Table 7. Selected variables for data mining technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1/1	1/8	1/15	1/22	1/29	2/5	2/12	2/19	2/26	3/5	3/12	3/19	3/26
Last day	1/7	1/14	1/21	1/28	2/4	2/11	2/18	2/25	¾	3/11	3/18	3/25	4/1
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	4/2	4/9	4/16	4/23	4/30	5/7	5/14	5/21	5/28	6/4	6/11	6/18	6/25
Last day	4/8	4/15	4/22	4/29	5/6	5/13	5/20	5/27	6/3	6/10	6/17	6/24	7/1
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	7/2	7/9	7/16	7/23	7/30	8/6	8/13	8/20	8/27	9/3	9/10	9/17	9/24
Last day	7/8	7/15	7/22	7/29	8/5	8/12	8/19	8/26	9/2	9/9	9/16	9/23	9/30
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	10/1	10/8	10/15	10/22	10/29	11/5	11/12	11/19	11/26	12/3	12/10	12/17	12/24
Last day	10/7	10/14	10/21	10/28	11/4	11/11	11/18	11/25	12/2	12/9	12/16	12/23	12/30

Table 8. Selected variables for data mining technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1/1	1/8	1/15	1/22	1/29	2/5	2/12	2/19	2/26	3/5	3/12	3/19	3/26
Last day	1/7	1/14	1/21	1/28	2/4	2/11	2/18	2/25	¾	3/11	3/18	3/25	4/1
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	4/2	4/9	4/16	4/23	4/30	5/7	5/14	5/21	5/28	6/4	6/11	6/18	6/25
Last day	4/8	4/15	4/22	4/29	5/6	5/13	5/20	5/27	6/3	6/10	6/17	6/24	7/1
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	7/2	7/9	7/16	7/23	7/30	8/6	8/13	8/20	8/27	9/3	9/10	9/17	9/24
Last day	7/8	7/15	7/22	7/29	8/5	8/12	8/19	8/26	9/2	9/9	9/16	9/23	9/30
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	10/1	10/8	10/15	10/22	10/29	11/5	11/12	11/19	11/26	12/3	12/10	12/17	12/24
Last day	10/7	10/14	10/21	10/28	11/4	11/11	11/18	11/25	12/2	12/9	12/16	12/23	12/30

Table 9. Final selected variables (aggregation of data mining techniques 1-3)

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1/1	1/8	1/15	1/22	1/29	2/5	2/12	2/19	2/26	3/5	3/12	3/19	3/26
Last day	1/7	1/14	1/21	1/28	2/4	2/11	2/18	2/25	¾	3/11	3/18	3/25	4/1
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	4/2	4/9	4/16	4/23	4/30	5/7	5/14	5/21	5/28	6/4	6/11	6/18	6/25
Last day	4/8	4/15	4/22	4/29	5/6	5/13	5/20	5/27	6/3	6/10	6/17	6/24	7/1
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	7/2	7/9	7/16	7/23	7/30	8/6	8/13	8/20	8/27	9/3	9/10	9/17	9/24
Last day	7/8	7/15	7/22	7/29	8/5	8/12	8/19	8/26	9/2	9/9	9/16	9/23	9/30
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	10/1	10/8	10/15	10/22	10/29	11/5	11/12	11/19	11/26	12/3	12/10	12/17	12/24
Last day	10/7	10/14	10/21	10/28	11/4	11/11	11/18	11/25	12/2	12/9	12/16	12/23	12/30

As it follows from Tables 6-9, certain week is included in the final efficient set of variables if it was selected by at least two data mining techniques. Final efficient set of weather variables for corn, grown in Haskell county, will consist of HDDs recorded over weeks 5 through 8, cumulative precipitations recorded over weeks 7 through 11, and 18 through 26, and CDDs recorded over weeks 23 through 27. Candidate variables and final time periods, over which weather variables are recorded, for all data mining techniques applied to all crop/locations combinations is presented in Tables A13 – A56 of appendixes.

Once the final time periods over which weather variables should be recorded are defined for each crop/location combination, the optimal copula to model joint weather/yield distribution should be identified.

According to Ghosh, Woodard, and Vedenov (2011), to date, copulas have primarily been viewed within "in-sample" fitting framework. But given the fact that ranking of univariate distributions for the purposes of fitting to data are subject to in-sample overfitting, there is a very high probability that ranking of copulas based merely on their in-sample performance might lead to erroneous conclusions regarding the ranking of copulas in empirical settings. Hence, following methodology proposed by Ghosh, Woodard, and Vedenov (2011) the ranking and fitting of copulas will be performed in out-of-sample efficient framework. Norwood, Roberts, and Lusk (2004) suggested using the out-of-sample log-likelihood functions (OSLL) for ranking of candidate distributions, where OSLL realizations are constructed by successively estimating the yield distribution model with holdout observation(s) and then evaluating the predicted density value at the out-of-sample observation(s). The candidate distributions are then evaluated based on their log-likelihood values. Once the out-of-sample efficient copula is identified, it is used to numerically derive generated farmer's profit distribution and calculate values of risk reduction metric (as it is defined in Section 3.1 of the thesis) under the optimal copula form, selected from 6 different alternatives (Gaussian, Student-t, Frank, Gumbel, Clayton, and Kernel).

This task is solved by finding the copula, which results in a form that is out-of-sample efficient. The term "out-of-sample efficient" is used to refer to the model that maximizes the out-of-sample log-likelihood function using a "leave-one-out" cross validation procedure. The out-of-sample criterion has the desirable asymptotic property that it maximizes the Kullback-Leibler Information Criterion (KLIC) (Woodard and Sherrick, 2011).

According to Woodard and Sherrick (2011) traditional in-sample distribution fitting approach results in model $M_k = \{f_k(x, \theta_k); \theta_k^*(Y)\}$, where M_k – k candidate distribution model available with a specific pdf, $f_k(x, \theta_k)$, and an estimator for the in-sample model parameters, $\theta_k^*(Y)$, given observational data Y, and observation x, at which to evaluate the pdf. The fitted pdf of model k given all in-sample data, Y, evaluated at x is then expressed as $f_k(x, \theta_k^*(Y))$. The in-sample likelihood for model k is then $L_k^{in} = \prod_{i=1}^{N} f_k(x, \theta_k^*(Y))$. The best likelihood measure implicitly "selects" the single candidate that optimizes this form of congruence. In the case of modeling out-of-sample yields and weather indexes, one wish to work with the subset of Y, where one observation is withheld from out-of-sample evaluation (y_{-i}). The out-of-sample fitted pdf for model k evaluated at the hold-out observation is denoted $f_{k,i}(y_i, \theta_k^*(y_{-i}))$. To truly represent the out-of-sample measures, the parameters must be functions of y_{-i} and not y_i. The OSLL for model k is then calculated as $L_k^{out} = \prod_{i=1}^{N} f_{k,i}(y_i, \theta_k^*(y_{-i}))$. Norwood, Roberts, and Lusk (2004) argue that a desirable objective is to select the optimal model k* such that $L_{k*}^{out} > L_k^{out} \; \forall \; k$.

Once the out-of-sample efficient copulas is identified, the full sample data of yields and corresponding weather indexes is employed with the optimal copula parameters θ^* to arrive at the final model pdf:

$$f_{final}^*(x|\theta^*, M, \eta) = f(x, \theta^*(\eta)) \qquad (45)$$

For each crop/county combination the parametric copulas are calibrated using Canonical Maximum Likelihood Method (CML). The CML method doesn't imply any a priory assumptions on the distributional form of the marginal and uses the empirical distribution for each of the n variables to convert each of the observed data $X_{T\times N}$ into uniform variates, $\hat{u}_{n,t}$. The CML method is implemented with a two-step procedure:

1. Transformation of the initial dataset $X = (X_{1t}, X_{2t}, \dots, X_{Nt})$, where t = 1,2,…,T into uniform variates, using the empirical marginal distribution:

   $$\hat{u}_t = (\hat{u}_1^t, \hat{u}_2^t, \dots, \hat{u}_N^t) = [\hat{F}_1(X_{1t}), \hat{F}_2(X_{2t}), \dots, \hat{F}_N(X_{Nt})], \tag{46}$$

   where F is the marginal distribution.

2. The copula parameters θ can be estimated using the following formula:

   $$\hat{\theta}_{CML} = argmax_{\theta} \sum_{t=1}^{T} \ln c(\hat{u}_1^t, \hat{u}_2^t, \dots, \hat{u}_N^t; \theta) \tag{47}$$

For the purposes of this research six different copulas, defined above, have been used. Once parameters of copula are estimated, 10,000 random numbers from the five different parametric copulas and the Kernel copula are generated. For the Kernel copula normal kernel and “rule of thumb” bandwidth are used. This provides correlated uniforms for each copula type. The inverse transformation method of the specified marginals for yields and corresponding weather indexes is used to get the simulated yields and weather indexes for each copula.

To identify the out-of-sample efficient copula the copula probability density of each copula model was calculated at the holdout observation. The parameters of each copula were calculated using the rest forty one observations. Then those parameters were used to calculate the density at the left over observation. After logarithmic transformation the copula densities are summed over all the forty two observations to arrive at the out-of-sample log-likelihood value for each copula. Results of OSLL calculation for different copulas and all crop/locations combinations are presented in Tables 10, 11, 12, and 13.

Table 10. Results of out-of-sample metric calculation for different copulas and all crop/locations combinations in Panhandle area of Texas

Area	County	Crop	Copula	Out-of-sample metric values
Panhandle	Castro	Corn	Kernel copula	3.29
			Gaussian copula	2.04
			t-copula	1.93
			Frank copula	2.94
			Gumbel copula	0.70
			Clayton copula	5.74
	Ochiltree	Wheat	Kernel copula	2.27
			Gaussian copula	3.85
			t-copula	3.79
			Frank copula	3.19
			Gumbel copula	4.02
			Clayton copula	3.34
	Lubbock	Cotton	Kernel copula	5.80
			Gaussian copula	9.05
			t-copula	9.59
			Frank copula	7.36
			Gumbel copula	9.33
			Clayton copula	6.86

Table 11. Results of out-of-sample metric calculation for different copulas and all crop/locations combinations in the area to the East from Panhandle in Texas

Area	County	Crop	Copula	Out-of-sample metric values
East from Panhandle	Williamson	Corn	Kernel copula	10.00
			Gaussian copula	11.14
			t-copula	11.77
			Frank copula	11.27
			Gumbel copula	8.77
			Clayton copula	14.63
	Haskell	Wheat	Kernel copula	14.91
			Gaussian copula	17.81
			t-copula	18.24
			Frank copula	18.75
			Gumbel copula	15.64
			Clayton copula	14.15
	Haskell	Cotton	Kernel copula	4.26
			Gaussian copula	8.02
			t-copula	7.02
			Frank copula	6.66
			Gumbel copula	7.78
			Clayton copula	8.24

Table 12. Results of out-of-sample metric calculation for different copulas and all crop/locations combinations in the East Texas area

Area	County	Crop	Copula	Out-of-sample metric values
East Texas	Robertson	Corn	Kernel copula	7.87
			Gaussian copula	9.14
			t-copula	9.24
			Frank copula	9.81
			Gumbel copula	7.75
			Clayton copula	6.72
	Bell	Wheat	Kernel copula	1.74
			Gaussian copula	1.97
			t-copula	0.10
			Frank copula	2.91
			Gumbel copula	2.59
			Clayton copula	1.57
	Robertson	Cotton	Kernel copula	6.15
			Gaussian copula	6.59
			t-copula	6.26
			Frank copula	6.70
			Gumbel copula	6.15
			Clayton copula	6.08

Table 13. Results of out-of-sample metric calculation for different copulas and all crop/locations combinations in the Coastal area of Texas

Area	County	Crop	Copula	Out-of-sample metric values
Coastal Area	Wharton	Corn	Kernel copula	5.89
			Gaussian copula	7.60
			t-copula	7.84
			Frank copula	7.75
			Gumbel copula	7.31
			Clayton copula	6.46
	Bee	Wheat	Kernel copula	3.15
			Gaussian copula	4.48
			t-copula	4.64
			Frank copula	3.44
			Gumbel copula	3.72
			Clayton copula	4.35
	Wharton	Cotton	Kernel copula	4.78
			Gaussian copula	5.61
			t-copula	6.04
			Frank copula	6.06
			Gumbel copula	5.99
			Clayton copula	6.50

As it is evident from Tables 10-13 the most optimal copula is crop and county specific. Clayton and Frank copulas tend to outperform all others in out-of-sample efficient framework (frequency of appearance 36%), followed by t-copula, and Gumbel (27% and 9% correspondingly). Once optimal copula is identified for each crop/location combinations it was used to model joint weather/yield distributions and to come up with final risk reduction values for the proposed contracts at the 85% coverage level, according to the methodology outlined in Section 3.1 of the thesis.

Table 14. Final results of risk-reduction calculation provided by the proposed weather contracts

Area	County	Crop	Final relative value of risk reduction, %
Panhandle	Castro	Corn	78.3
	Ochiltree	Wheat	71.3
	Lubbock	Cotton	58.5
East from Panhandle	Williamson	Corn	58.0
	Haskell	Wheat	45.0
	Haskell	Cotton	61.5
East Texas	Robertson	Corn	56.7
	Bell	Wheat	73.2
	Robertson	Cotton	56.9
Coastal Area	Wharton	Corn	66.0
	Bee	Wheat	61.8
	Wharton	Cotton	67.3

Results of risk reduction calculation (Table 14), computed using whole sample of data and optimal copula for a given crop/location combination, suggest that effective management of weather risks by the means of proposed in this thesis weather derivatives is possible in the state of Texas, and that on average geographically the most significant results could be obtained in the Panhandle area of Texas, while crop wise the most significant results could be obtained for corn.

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Existing programs of crop insurance administrated by Risk Management Agency of USDA remain largely ineffective and expensive. This was major reason why in the recent decade weather derivatives and their application for risk management in agriculture has drawn significant attention from researchers and practitioners from all over the world. However major problems associated with weather derivatives didn't allow products, based on weather derivatives, become efficient instrument of risk reduction. This research summarizes accumulated knowledge about application of weather derivatives to risk management in agriculture and attempts to expand methodology proposed by the most renowned agricultural economists.

It was shown that construction of weather derivatives based on shorter time periods, rather than ad hoc selected summer months or season, can allow for more careful selection of candidate weather variables and final time periods, used to specify weather variables included in the final model. In addition, it was proven that application of copulas may help in more accurate modeling of joint weather/yield distributions. Finally selection of the optimal copula should be based on its out-of-sample performance. Application of these two innovations to construction of crop insurance products based on weather derivatives should significantly reduce technological basis risk, what, in addition with earlier proposed methodologies aimed at reduction of geographical basis, hopefully will contribute to more rapid development of weather derivatives market for agricultural producers in the future.

Analysis of efficiency of proposed weather derivatives contracts for the purposes of this thesis was limited to the selected counties of Texas. It will be interesting to see how proposed methodology would work in other major crop producing regions of the USA and other parts of the world. In addition, assessment of efficiency of weather derivatives on the farmer's level might create significant interest for future researchers.

Absence of relevant benchmark doesn't allow for comparison of proposed contracts to existing risk reduction products. Comparison of proposed contracts to the products based on weather variables, selected using ad hoc procedures (e.g. Vedemov and Barnett, 2004), or to existing crop insurance products (e.g. Group Risk Plan - GRP), might create deeper insight into effectiveness of proposed contracts and, more importantly, their future in the market place.

In addition, optimal mixing of copulas proposed by Ghosh, Woodard, and Vedenov (2011) could be the next step in more effective modeling of joint weather/yield distributions for the purposes of weather derivatives risk reduction assessment in agriculture.

Finally, performance of the proposed contracts could be improved using more appropriate functional form, employed in construction of weather indexes.

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APPENDIX A

A-1. Premium and maximum indemnity for contracts based on data mining technique 1

	Technique 1 (Correlation)					
	Premium			Max indemnity		
Model	wheat	cotton	corn	wheat	cotton	corn
1 week	1.34	8.42	13.40	128.39	225.46	229.84
2 weeks	1.30	7.97	10.14	128.21	224.57	228.53
3 weeks	1.56	7.08	10.37	128.09	224.84	228.14
4 weeks	1.79	8.97	8.41	128.23	225.09	226.73
5 weeks	2.34	7.13	7.23	128.41	224.26	226.58
seasonal	2.74	6.59	3.62	128.24	224.31	224.71

A-2. Premium and maximum indemnity for contracts based on data mining technique 2

	Technique 2 (AIC)					
	Premium			Max indemnity		
Model	wheat	cotton	corn	wheat	cotton	corn
1 week	2.96	13.39	15.28	128.75	228.08	232.15
2 weeks	2.78	11.42	12.70	128.70	227.12	230.11
3 weeks	3.15	4.20	11.32	128.75	223.39	228.33
4 weeks	2.41	6.19	11.58	128.45	224.43	228.05
5 weeks	2.82	10.38	10.86	128.71	225.33	228.72
seasonal	2.56	6.72	2.71	128.38	223.55	224.69

A-3. Premium and maximum indemnity for contracts based on data mining technique 3

	Technique 3 (PC algorithm)					
	Premium			Max indemnity		
Model	wheat	cotton	corn	wheat	cotton	corn
1 week	0.94	4.80	13.73	128.33	224.54	230.95
2 weeks	1.85	4.99	10.05	128.42	223.37	227.69
3 weeks	2.14	4.86	9.67	128.24	223.21	227.19
4 weeks	1.79	7.22	9.49	128.12	224.49	227.03
5 weeks	2.29	6.85	7.96	128.36	223.89	226.41
seasonal	2.58	6.17	2.51	128.25	223.44	224.46

A-4. Selected variables and absolute risk reduction for contracts for wheat based on data mining technique 1

Model	Wheat_Haskell couny_Technique 1 (Correlation)				
	Selected variables	R-square	OOS MSE	delta	
				G-copula	T-copula
1 week	HDD_week_12, CDD_week_29, CDD_week_40; Prcp_week_26, Prcp_week_34, Prcp_week_40	0.60	1.83	51.93	62.59
2 weeks	HDD_week_11to12, CDD_week_29to30, CDD_week_39to40; Prcp_week_25to26, Prcp_week_33to34, Prcp_week_39to40	0.55	3.39	46.37	61.98
3 weeks	HDD_week_7to9, CDD_week_28to30, CDD_week_40to42; Prcp_week_25to27, Prcp_week_28to30, Prcp_week_37to39	0.52	2.89	51.59	70.20
4 weeks	HDD_week_9to12, CDD_week_29to32, CDD_week_37to40; Prcp_week_25to28, Prcp_week_29to32, Prcp_week_37to40	0.57	2.27	62.06	82.44
5 weeks	HDD_week_11to15, CDD_week_31to35, CDD_week_36to40; Prcp_week_26to30, Prcp_week_31to35, Prcp_week_36to40	0.64	1.63	90.06	107.24
seasonal	CDD_seasonal; Prcp_seasonal	0.60	1.12	87.37	114.15

A-5. Selected variables and absolute risk reduction for contracts for wheat based on data mining technique 2

Model	Wheat_Haskell couny_Technique 2 (AIC)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	Prcp_week_12, HDD_week_33, Prcp_week_29; Prcp_week_34, CDD_week_40, Prcp_week_25	0.76	135.26	152.07
2 weeks	Prcp_week_11to12, Prcp_week_25to26, Prcp_week_29to30; Prcp_week_33to34, CDD_week_39to40, CDD_week_33to34	0.73	121.16	135.35
3 weeks	Prcp_week_4to6, Prcp_week_22to24, Prcp_week_25to27; Prcp_week_28to30, Prcp_week_31to33, CDD_week_34to36	0.76	140.59	152.36
4 weeks	Prcp_week_9to12, Prcp_week_21to24, Prcp_week_25to28; Prcp_week_29to32, CDD_week_37to40, CDD_week_41to44	0.65	93.73	113.17
5 weeks	Prcp_week_1to5, Prcp_week_11to15, Prcp_week_21to25; Prcp_week_26to30, Prcp_week_31to35, CDD_week_41to45	0.74	126.47	139.07
seasonal	CDD_seasonal, HDD_seasonal; Prcp_seasonal	0.63	91.68	111.37

A-6. Selected variables and absolute risk reduction for contracts for wheat based on data mining technique 3

Model	Wheat_Haskell couny_Technique 3 (PC algorithm)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	HDD_week35, CDD_week29, CDD_week40; Prcp_week12, Prcp_week26, Prcp_week29	0.63	58.22	70.16
2 weeks	CDD_week39-40; Prcp_week11-12, Prcp_week25-26, Prcp_week29-30, Prcp_week33-34	0.69	104.39	119.98
3 weeks	CDD_week28-30; Prcp_week4-6, Prcp_week22-24, Prcp_week25-27, Prcp_week28-30	0.66	100.85	118.32
4 weeks	HDD_week9-12, CDD_week37-40; Prcp_week9-12, Prcp_week21-24, Prcp_week25-28, Prcp_week29-32	0.61	79.57	99.48
5 weeks	HDD_week11-15, CDD_week36-40; Prcp_week1-5, Prcp_week11-15, Prcp_week21-25, Prcp_week26-30	0.68	98.62	111.78
seasonal	CDD_seasonal; Prcp_seasonal	0.63	96.77	115.35

A-7. Selected variables and absolute risk reduction for contracts for cotton based on data mining technique 1

Model	Cotton_Haskell couny_Technique 1 (Correlation)				
	Selected variables	R-square	OOS MSE	delta	
				G-copula	T-copula
1 week	HDD_week_14, CDD_week_20, CDD_week_27; Prcp_week_12, Prcp_week_24, Prcp_week_33	0.51	7.83	454.37	576.80
2 weeks	CDD_week_13to14, CDD_week_19to20, CDD_week_27to28; Prcp_week_13to14, Prcp_week_23to24, Prcp_week_33to34	0.44	6.99	333.53	486.96
3 weeks	CDD_week_13to15, CDD_week_25to27, CDD_week_28to30; Prcp_week_10to12, Prcp_week_22to24, Prcp_week_28to30	0.46	5.27	342.16	496.19
4 weeks	CDD_week_9to12, CDD_week_17to20, CDD_week_25to28; Prcp_week_9to12, Prcp_week_21to24, Prcp_week_33to36	0.48	5.48	422.24	529.68
5 weeks	CDD_week_6to10, CDD_week_16to20, CDD_week_26to30; Prcp_week_11to15, Prcp_week_16to20, Prcp_week_26to30	0.41	5.48	308.48	423.88
seasonal	CDD_seasonal; Prcp_seasonal	0.41	3.47	267.81	411.63

A-8. Selected variables and absolute risk reduction for contracts for cotton based on data mining technique 2

Model	Cotton_Haskell couny_Technique 2 (AIC)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	CDD_week_11, Prcp_week_12, Prcp_week_24; Prcp_week_28, Prcp_week_33, CDD_week_14	0.72	1010.99	1069.16
2 weeks	CDD_week_9to10, CDD_week_11to12, Prcp_week_17to18; CDD_week_27to28, CDD_week_29to30, Prcp_week_27to28	0.63	734.60	826.16
3 weeks	CDD_week_30to31, CDD_week_41to45, CDD_week_42to46; CDD_week_37to38, CDD_week_38to39, CDD_week_32to33	0.33	172.59	262.29
4 weeks	CDD_week_47to48, CDD_week_50to51, CDD_week_51to52; Prcp_week_50to51, Prcp_week_1to3, CDD_week_1to3	0.46	224.51	415.43
5 weeks	CDD_week_22to24, CDD_week_21to26, CDD_week_25to27; Prcp_week_28to30, Prcp_week_34to36, CDD_week_34to36	0.51	517.37	623.86
seasonal	CDD_seasonal, HDD_seasonal; Prcp_seasonal	0.37	234.62	373.31

A-9. Selected variables and absolute risk reduction for contracts for cotton based on data mining technique 3

Model	Cotton_Haskell couny_Technique 3 (PC algorithm)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	CDD_week27; Prcp_week12, Prcp_week24, Prcp_week33	0.42	269.26	378.61
2 weeks	CDD_week9-10; Prcp_week27-28, Prcp_week29-30, Prcp_week33-34	0.43	333.01	461.26
3 weeks	CDD_week25-27, CDD_week28-30; Prcp_week10-12, Prcp_week28-30	0.43	311.84	466.18
4 weeks	CDD_week9-12, CDD_week25-28, CDD_week33-36; Prcp_week9-12, Prcp_week25-28, Prcp_week33-36	0.51	484.43	585.31
5 weeks	CDD_week11-15, CDD_week26-30; Prcp_week26-30, Prcp_week31-35	0.40	305.41	412.41
seasonal	CDD_seasonal; Prcp_seasonal	0.41	273.94	409.16

A-10. Selected variables and absolute risk reduction for contracts for corn based on data mining technique 1

Model	Corn_Haskell couny_Technique 1 (Correlation)				
	Selected variables	R-square	OOS MSE	delta	
				G-copula	T-copula
1 week	HDD_week_6, HDD_week_15, Prcp_week_9; CDD_week_25, Prcp_week_17, Prcp_week_24	0.62	10.41	895.06	947.31
2 weeks	HDD_week_5to6, HDD_week_15to16, Prcp_week_3to4; CDD_week_25to26, Prcp_week_13to14, Prcp_week_19to20	0.52	7.75	551.12	645.66
3 weeks	HDD_week_4to6, HDD_week_16to18, Prcp_week_7to9; CDD_week_25to27, Prcp_week_13to15, Prcp_week_19to21	0.50	9.75	534.65	627.41
4 weeks	HDD_week_5to8, HDD_week_13to16, Prcp_week_5to8; CDD_week_25to28, Prcp_week_13to16, Prcp_week_21to24	0.40	9.57	356.86	464.75
5 weeks	HDD_week_6to10, HDD_week_11to15, Prcp_week_6to10; CDD_week_21to25, Prcp_week_11to15, Prcp_week_21to25	0.38	6.66	285.57	391.21
seasonal	CDD_seasonal; Prcp_seasonal	0.25	4.94	76.13	176.50

A-11. Selected variables and absolute risk reduction for contracts for corn based on data mining technique 2

Model	Corn_Haskell couny_Technique 2 (AIC)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	Prcp_week_9, Prcp_week_10, CDD_week_25; Prcp_week_20, Prcp_week_24, Prcp_week_28	0.76	1317.55	1315.47
2 weeks	HDD_week_5to6, CDD_week_17to18, CDD_week_25to26; Prcp_week_19to20, Prcp_week_23to24, HDD_week_9to10	0.63	881.44	932.17
3 weeks	Prcp_week_7to9, CDD_week_13to15, CDD_week_25to27; Prcp_week_19to21, Prcp_week_22to24, HDD_week_4to6	0.52	610.95	699.03
4 weeks	HDD_week_5to8, HDD_week_9to12, CDD_week_25to28; Prcp_week_17to20, Prcp_week_21to24, CDD_week_13to16	0.51	591.02	691.73
5 weeks	HDD_week_6to10, CDD_week_26to30, Prcp_week_16to20; Prcp_week_21to25, Prcp_week_26to30, CDD_week_11to15	0.53	617.58	698.43
seasonal	CDD_seasonal, HDD_seasonal; Prcp_seasonal	0.24	99.80	145.01

A-12. Selected variables and absolute risk reduction for contracts for corn based on data mining technique 3

Model	Corn_Haskell couny_Technique 3 (PC algorithm)			
	Selected variables	R-square	delta	
			G-copula	T-copula
1 week	HDD_week7, CDD_week25; Prcp_week3, Prcp_week9, Prcp_week20, Prcp_week21, Prcp_week24	0.75	1367.71	1365.86
2 weeks	CDD_week25-26; Prcp_week3-4, Prcp_week19-20, Prcp_week23-24	0.51	557.46	656.25
3 weeks	CDD_week25-27; Prcp_week19-21, Prcp_week22-24	0.46	490.88	584.77
4 weeks	HDD_week5-8, CDD_week21-24, CDD_week25-28; Prcp_week17-20, Prcp_week21-24	0.48	553.65	642.46
5 weeks	CDD_week21-25; Prcp_week16-20, Prcp_week21-25	0.40	341.79	429.27
seasonal	CDD_seasonal; Prcp_seasonal	0.25	77.26	164.10

A-13. Candidate weather variables for cotton, Haskell county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-14. Candidate weather variables for cotton, Haskell county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-15. Candidate weather variables for cotton, Haskell county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-16. Final weather variables for cotton, Haskell county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-17. Candidate weather variables for wheat, Haskell county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-18. Candidate weather variables for wheat, Haskell county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-19. Candidate weather variables for wheat, Haskell county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-20. Final weather variables for wheat, Haskell county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-21. Candidate weather variables for corn, Castro county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-22. Candidate weather variables for corn, Castro county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-23. Candidate weather variables for corn, Castro county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-24. Final weather variables for corn, Castro county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-25. Candidate weather variables for cotton, Lubbock county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-26. Candidate weather variables for cotton, Lubbock county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-27. Candidate weather variables for cotton, Lubbock county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-28. Final weather variables for cotton, Lubbock county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-29. Candidate weather variables for wheat, Ochiltree county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-30. Candidate weather variables for wheat, Ochiltree county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-31. Candidate weather variables for wheat, Ochiltree county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-32. Final weather variables for wheat, Ochiltree county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-33. Candidate weather variables for corn, Robertson county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-34. Candidate weather variables for corn, Robertson county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-35. Candidate weather variables for corn, Robertson county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-36. Final weather variables for corn, Robertson county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-37. Candidate weather variables for cotton, Robertson county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-38. Candidate weather variables for cotton, Robertson county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-39. Candidate weather variables for cotton, Robertson county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-40. Final weather variables for cotton, Robertson county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-41. Candidate weather variables for wheat, Bell county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-42. Candidate weather variables for wheat, Bell county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-43. Candidate weather variables for wheat, Bell county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-44. Final weather variables for wheat, Bell county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-45. Candidate weather variables for corn, Wharton county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-46. Candidate weather variables for corn, Wharton county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-47. Candidate weather variables for corn, Wharton county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-48. Final weather variables for corn, Wharton county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-49. Candidate weather variables for cotton, Wharton county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-50. Candidate weather variables for cotton, Wharton county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-51. Candidate weather variables for cotton, Wharton county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-52. Final weather variables for cotton, Wharton county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Jan	8-Jan	15-Jan	22-Jan	29-Jan	5-Feb	12-Feb	19-Feb	26-Feb	5-Mar	12-Mar	19-Mar	26-Mar
Last day	7-Jan	14-Jan	21-Jan	28-Jan	4-Feb	11-Feb	18-Feb	25-Feb	4-Mar	11-Mar	18-Mar	25-Mar	1-Apr
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	2-Apr	9-Apr	16-Apr	23-Apr	30-Apr	7-May	14-May	21-May	28-May	4-Jun	11-Jun	18-Jun	25-Jun
Last day	8-Apr	15-Apr	22-Apr	29-Apr	6-May	13-May	20-May	27-May	3-Jun	10-Jun	17-Jun	24-Jun	1-Jul
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Jul	9-Jul	16-Jul	23-Jul	30-Jul	6-Aug	13-Aug	20-Aug	27-Aug	3-Sep	10-Sep	17-Sep	24-Sep
Last day	8-Jul	15-Jul	22-Jul	29-Jul	5-Aug	12-Aug	19-Aug	26-Aug	2-Sep	9-Sep	16-Sep	23-Sep	30-Sep
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Oct	8-Oct	15-Oct	22-Oct	29-Oct	5-Nov	12-Nov	19-Nov	26-Nov	3-Dec	10-Dec	17-Dec	24-Dec
Last day	7-Oct	14-Oct	21-Oct	28-Oct	4-Nov	11-Nov	18-Nov	25-Nov	2-Dec	9-Dec	16-Dec	23-Dec	30-Dec

A-53. Candidate weather variables for wheat, Bee county, technique 1

Technique 1 (correlation)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-54. Candidate weather variables for wheat, Bee county, technique 2

Technique 2 (AIC)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-55. Candidate weather variables for wheat, Bee county, technique 3

Technique 3 (PC algorithm)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

A-56. Final weather variables for wheat, Bee county, combined techniques

Combined techniques (final)													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
First day	1-Sep	8-Sep	15-Sep	22-Sep	29-Sep	6-Oct	13-Oct	20-Oct	27-Oct	3-Nov	10-Nov	17-Nov	24-Nov
Last day	7-Sep	14-Sep	21-Sep	28-Sep	5-Oct	12-Oct	19-Oct	26-Oct	2-Nov	9-Nov	16-Nov	23-Nov	30-Nov
	14	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**
First day	1-Dec	8-Dec	15-Dec	22-Dec	29-Dec	5-Jan	12-Jan	19-Jan	26-Jan	2-Feb	9-Feb	16-Feb	23-Feb
Last day	7-Dec	14-Dec	21-Dec	28-Dec	4-Jan	11-Jan	18-Jan	25-Jan	1-Feb	8-Feb	15-Feb	22-Feb	1-Mar
	27	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**
First day	2-Mar	9-Mar	16-Mar	23-Mar	30-Mar	6-Apr	13-Apr	20-Apr	27-Apr	4-May	11-May	18-May	25-May
Last day	8-Mar	15-Mar	22-Mar	29-Mar	5-Apr	12-Apr	19-Apr	26-Apr	3-May	10-May	17-May	24-May	31-May
	40	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**	**49**	**50**	**51**	**52**
First day	1-Jun	8-Jun	15-Jun	22-Jun	29-Jun	6-Jul	13-Jul	20-Jul	27-Jul	3-Aug	10-Aug	17-Aug	24-Aug
Last day	7-Jun	14-Jun	21-Jun	28-Jun	5-Jul	12-Jul	19-Jul	26-Jul	2-Aug	9-Aug	16-Aug	23-Aug	30-Aug

VITA

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